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Universidad del País Vasco Euskal Herriko Unibertsitatea

PhD Thesis:

FLBEIA fisheries management simulation model. Definition of new criteria and guidelines for efficient validation of the model using global sensitivity analysis.

Dorleta García

2020

Supervised by:
Inmaculada Arostegui
Raúl Prellezo

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azti tecnalia

FLBEIA by AZTI

Irati eta Libe-ri
A mis padres,
Ekaitzeri,
Martari

Eskerrak, Agradecimientos, Acknowledgements

Heldu da momentua tesi honeri amaiera emateko. Ez dut gure amaitu prosezu luze honetan lagundu nauzuenei eta bizitza alaiago eta errezago egin didazuenei eskerrak eman barik. Bizitza zuen moduko gentearekin konpartitzea ez du preziorik.

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Laburpena

Tesi hau Europako Batzordeko arrantza batzorde zientifiko, tekniko eta ekonomikoak identifikatutako simulazio bioekonomikoko eredu integratuak garatzeko beharrak eragin zuen. Eredu horiek aplikatzeko esparrua arrantza kudeatzeko estrategien inpaktu-analisia izan behar zen. Gainera, arrantza-kudeaketako estrategia eremu zabal batean aplikatzeko bezain orokorra eta generikoa izan behar zuen, eta kudeaketa-estrategien ebaluazio (management strategy evaluation, MSE, ingeleszko sigletan deritzona) metodologiari (Punt et al. 2016) jarraitu behar zion.

Sistema naturalak deskribatzen duten eredu matematikoak deskribatzen duten sistemaren abstrakzioak dira, eta inoiz ezin dute sistema erreala modu perfektuan deskribatu. Aitzitik, ezarritako helbururako ereduak modelatutako sistema egoki irudikatzea da behar dena (Rykiel 1996). Ereduen egokitasuna ebaluatzeko prozesuari balioztapena deritzo. Hala ere, ez dago ereduak egokiak direla erabat bermatzeko erabil daitekeen prozedurarik. Balioztatzea, ereduaren garapen osoan zehar gertatzen den prozesua da (Sargent 2011). Sentikortasun-analisi globala (global sensitivity analysis, GSA, ingelesezko sigletan) simulazio-ereduen balioztapenean aurrera egiteko erabil daitekeen teknika kuantitatiboa da (ikusi Norton 2015, Borgonovo eta Plischke 2016 edo Pianosi et al. 2016 azken urteetako errebisioetarako). GSA simulazio ereduen irteerako aldakortasuna sarrera-faktoreen aldakortasunaren arabera azaltzean datza.

Simulazio bioekonomikoko ereduen beharra asetzeko, `FLBEIA` (Bio-Economic Impact Assessment in `FLR`) garatu genuen. Simulazio-ereduen garapenean balioztapenak duen garrantzia kontuan hartuta, tesi honek bi helburu ditu: lehenik, `FLBEIA` garatzea, stock eta flota [1] anitzeko simulazio-eredua, MSE ikuspegiari jarraitzen

[1] *stock* arrain-populazio baten kudeaketa-unitate bateri deritzo eta *flota* karakteristika tekniko berdinak konpartitzen duen itsasontzi multzoa da.

diona; eta bigarren, haren balioztapenean aurrera egitea GSA erabiliz, arrantzako-simulazio ereduetan metodologia horren erabilera sustatzen den bitartean.

Halaber, arrantza-kudeaketa simulatzeko ereduak eta GSA metodoak aplikatzeari dagokionez, tesi honek hiru hipotesi planteatzen ditu:

- Ohi ziurgabetzat hartzen diren sarrera-faktoreak ez dira beti garrantzitsuenak.
- GSA metodo kuantitatiboetarako existizen diren konbergentzia-irizpideek ez dituzte egoera guztiak kontutan hartzen.
- Dimentsio anitzeko irteera duten ereduetan, sarrera-faktore garrantzitsuenen hautaketarako baheketa-metodoen aplikazioa alboratuta dago.

Sarreran, tesiaren edukia testuinguruan ipintzeko, haren lau zutabeei buruzko berrikuspena egin dugu: arrantza-kudeaketa, MSE, ereduen balioztapena eta GSA. Arrantza-kudeaketari buruz egindako berrikuspen bibliografikoak hurrengo artikulu zientifikoa sortarazi du: *"Contribution of mathematics to fisheries management throughout history"*. Artikulua prestatzen ari gara eta *"Fish and Fisheries"* aldizkarira bidaliko dugu.

Sarreraren ondoren, bigarren kapituluak `FLBEIA` ereduaren deskribapen zehatza ematen du, nola kodetu den eta eredua osatzen duen prozesu bakoitza deskribatzeko erabilitako ekuazioak aurkeztuz. `FLBEIA` eredua `R` estatistika-softwarea eta `FLR` paketeak erabiliz kodetu da, eta software bereko pakete gisa banatzen da. Eredua garatzen hasteko unean, eredu gehienak arrantza-sistemaren osagai biologikoa desbribatzen zuten, inolako osagai ekonomiko barik edo oso sinplea, edo alderantziz, osagai ekonomiko osoa, osagai biologiko sinpleaz. Beraz, `FLBEIA` MSE marko baten pean arrantza-sistemaren bi osagai horiek orekatzeko sortua izan zen, "ekosistemak ebaluatzeko konplexutasun ertaineko eredu" gisa sailka daitekelarik (Plagányi et al. 2014), arrantza-jardueraren kudeaketan ardazten dena, arrantza mistoen testuinguru batean. Ereduaren deskribapena *SoftwareX* aldizkari zientifikoan argitaratu da: *"`FLBEIA`: a simulation model to conduct bio-economic evaluation of fisheries management strategies"*, (Garcia et al. 2017b).

Tesiaren bigarren zatian, ereduaren balioztapenari erreparatu genion, eta GSA metodologia aukeratu genuen `FLBEIA`-n konfiantza sortzeko prozesuan aurrera egiteko. Egile askok (Homma eta Saltelli 1996, Sarrazin et al. 2016) erreferentziazko metodotzat hartzen dute Sobolen bariantzaren deskonposizio-metodoa, eta, beraz, hasieran GSA aplikatzeko, Sobolen metodoa soilik erabiltzea pentsatu genuen. Hala ere, bere kostu konputazional handiak beste aukera batzuk kontuan hartzera eraman gintuen. Literaturan emandako gomendioei jarraituz (Confalonieri et al. 2010, Saltelli et al. 2008), Sobolen metodoa Morrisen baheketa-metodoarekin konbinatzea erabaki genuen, sarrera-faktoreen kopurua murrizteko. Bi metodoak konbinatzean, modu robustoan egingo zela bermatzearen arazoari aurre egin behar izan genion. Hau da, aukeratutako sarrera-faktoreak benetan garrantzitsuenak zirela bermatzea.

Alde batetik, Morrisen metodoan sarrerako faktore garrantzitsuenen hautaketa bisualki egiten da, sarrera faktoreen *oinarrizko efektuen batez besteko balio absolutua* gainerakoetatik bereizten direnak aukeratuz (Campolongo et al. 2007). Dimentsio anitzeko irteera duten ereduetan, ereduaren irteera-aldagai bakoitzerako egiten da hautaketa, eta aldagai bakoitzerako hautatutako sarrera-faktoreen multzoak, multzo bakar batean biltzen dira. Arazoa da, irteera-aldagai asko daudenean, zaila dela hautaketa bisuala konstante mantentzea. Gainera, hautaketa bisuala ezin da erabili bootstrap bezalako simulazio metodoetan. Arazo hori gainditzeko, hautaketa-irizpide berri bat garatu genuen, irizpide horrek hautaketa bisuala egitean kontuan hartzen diren hiru aspektuetan oinarritzen da: hautatutako sarrera-faktoreen kopuruan, *oinarrizko efektuen batez besteko balio absolutua*n balio maximoarekin alderatuta, eta ondoz ondoko faktoreen *oinarrizko efektuen batez besteko balio absolutue*tan dagoen aldea. Bestalde, GSA metodoetarako dauden konbergentzia-irizpideek sentikortasun-indizeen balioan, horien sailkapenean edo sailkapenaren behealdean dauden indizeen konbergentzian jartzen dute arreta (Sarrazin et al. 2016). Hala ere, tesi honetan Morrisen metodoa aplikatzearen helburua ezberdina zen, hau da, sailkapenaren goikaldean dauden sarrera-faktoreak identifikatzea, horien posizio edo balio zehatzari garrantzia emon barik. Sarrazin et al. (2016)-en agertzen diren helburuak zorrotzagoak direnez, lotutako konbergentzia-irizpideen erabilerak gainzama konputazionala sor lezake. Beraz, ezarritako helbururako bereziki diseinatutako konbergentzia-irizpide berri bat definitu genuen. Tesi honetan proposatutako bi irizpide berri horiek, hain zuzen hautaketa-irizpidea eta konbergentzia-irizpidea, 3. kapituluan deskribatzen dira, eta horien deskribapena eta funtzionamenduaren ebaluazioa *Environmental Modeling & Software* aldizkari zientifikoan argitaratu dira: *"Robust combination of the Morris and Sobol methods in complex multidimensional models"*,(Garcia et al. 2019a).

Garatutako metodologiaren aplikazioa 4. kapituluan hasten da. Kapitulu honetan, `FLBEIA`-ren aplikazioa, Iberiar penintsularen alde atlantikoaren inguruan jarduten duen demertsal arrantzan, aurkezten da. Aplikazio horretan, arrantza-sistemaren errendimendu bioekonomikoa bi kudeaketa-politikarekin alderatzen dugu: batetik, Europako arrantza-politika bateratuaren azken erreforman sartutako lehorreratzeko betebeharraren politika (i.e harrapatutako arrainak itsasora botatzeko debekua), eta, bestetik, harrapatutako arrainak itsasora botatzea baimentzen zuen aurreko politika. Gainera, arrantza kudeatzeko erreferentzia-puntu berriak zehaztu genituen, eta politika berriaren eragin negatiboa arintzeko erabil ote zitezkeen probatu genuen. Lehorreratzeko betebeharraren inpaktua denboraldiaren eta flotaren araberakoa zela, eta haien dinamika eragin handia zuela ondorioztatu genuen. Arrantza osoari dagokionez, erreferentzia-puntu berriek lehorreratzeko betebeharra ezartzeak sortutako etekin ekonomikoen murrizketa arindu zuten. Hala ere, flota mailan, eragina flotaren eta kontuan hartutako denbora tartearen araberakoa zen. Kapitulu honen edukia *ICES journal of Marine Science* aldizkari zientifikoan argitaratu da: *"Bio-economic multi-stock reference points as a tool for overcoming the drawbacks of the landing obligation"*, (Garcia et al. 2017a).

Bostgarren kapituluan, hirugarren kapituluan proposatutako irizpideak eta jarraibideak probatu ziren, laugarren kapituluan aurkeztutako `FLBEIA` inplementazioan. Hirugarren kapituluko jarraibideak erabiliz, eredua parametrizatu egin zen, eta sarrera-faktoreen benetako kopurua %90a murriztu zen. Sarrera-faktoreen aldakortasuna laugarren kapituluan erabilitako batez besteko balioa eta %30eko aldakuntza-koefizientea erabiliz parametrizatu zen. Hirugarren kapituluan definitutako hautaketa- eta konbergentzia-irizpideak Morrisen *oinarrizko efektuen batez besteko balio absolutu*ei aplikatu zitzaizkien, irteerako 37 aldagairen gainean. Ondoren, Sobol metodoa aplikatu zen soilik Morris metodoaren bidez aukeratutako sarrera-faktoreak kontuan hartuz. Irteerako aldagai gehienen bariantza sarrera-faktoreen arteko korrelazioaren ondorio zen. Gainera, emaitzak stockaren eta flotaren menpekoak ziren. Bariantza globalaren deskonposizioa Lamboni et al. (2011)-k proposatutako metodoa erabiliz kalkulatu zen. Oro har, emaitzetan eragin handiena zuten sarrerako faktoreak floten epe laburreko dinamikarekin lotutakoak izan ziren (zenbat arrantza esfortsu egin eta nola zelan banatu), eta baita arrain stocken hilkortasun naturala eta pisua ere. Aitzitik, stocken erreklutamenduari zuzenean lotutako sarrera-faktoreak (ziurgabetasunaren parametrizazioan literaturak arreta gehien jartzen duen parametroak) sailkapenaren behealdean zeuden. Sistemaren kudeaketa-prozesuan egindako erroreekin lotutako sarrerako faktoreetatik, ikerketaren bidez murriztu daitezkeenetatik, sailkapenaren goiko aldean zeuden bakarrak, arrantzarako objetiboa diren stocketakoak ziren. Tesi honen idazketa amaitzean, artikulu bat idazten ari gara, GSA eta MSE metodologiak konbinatzearen potentziala nabarmenduz, eta analisi bien konbinazioan lortutako emaitzak erakutsiz. Artikulua *Methods in Ecology and Evolution* aldizkarira bidaliko da: *"Potential of applying global sensitivity analysis to fisheries management simulation models"* .

Seigarren kapituluan, tesiaren esparruan garatutako tresnak aurkezten ditugu, doan eskuragarri daudenak. Kapituluaren edukia teknikoa da eta ezagutza transferitzen laguntzen du, `FLBEIA` eta tesi honetan garatutako irizpideen erabilera erraztuz. Bigarren eta hirugarren kapituluetan `FLBEIA` eraikitzeko eta hautaketa- eta konbergentzia-irizpideak definitzeko erabilitako egitura eta formulak azaltzen badira, kapitulu honetan praktikan nola erabili erakusten dugu. `FLBEIA` paketearen osagarri gisa, Shiny aplikazio bat ere garatu dugu, emaitzen analisia errazteko. Kapitulu honetan, azken hau nola erabili ere erakusten dugu. Azkenik, Morris eta Sobol metodoen aplikazioan lortutako emaitza guztiak Shiny aplikazio batean kokatu dira, sentikortasun-indizeetan patroiak identifikatzea izugarri erraztu zuena.

Arrantza kudeaketa simulatzeko stock eta flota anitzeko ereduei esker, kudeaketa-estrategiek arrantza-sistemetan duten inpaktua aurreikus daiteke. Hortaz, oinarri zientifikoa ematen dute erabakiak hartzeko prozesuan laguntzeko, arrantza-sistemaren dimentsio biologikoa, ekonomikoa eta soziala esparru berean integratuz. Lehen, kudeaketa erabakiak kontsiderazio biologikoetan oinarritzen ziren nagusiki. Hala ere, ekosisteman oinarritutako arrantza-kudeaketak bultzatuta (Pikitch et al. 2004), dimentsio ekonomiko eta sozialak kontutan hartzea ezinbestekoa bihurtu da. Beraz, `FLBEIA` motako ereduak tresna baliotsu bihurtu dira kudeaketa-erabakiak sostengatzeko. Eredu horien erabileran dagoen arazo nagusietako bat arrantza-sistemen modelizazio matematikoan dagoen ziurgabetasun handia da. Ziurgabetasuna sisteman dagoen aldakortasun naturalatik eta haren behaketan egindako erroreetatik dator. MSE metodologiak ziurgabetasun horiek guztiak erabakiak hartzeko prozesuan txertatzeko esparrua ematen du. Era berean, GSA ziurgabetasunak ereduen funtzionamenduan duen inpaktua karakterizatzeko tresna bat da. GSA eta MSE metodologiak, ordea, gutxitan konbinatzen dira arrantza-kudeaketaren simulazio ereduetan. Beraz, tesi honek arrantza-kudeaketan erabakiak hartzeko prozesua laguntzeko tresna berri bat eraiki ezezik, praktikan arrantza-simulazioko ereduen erabilera hobetzeko metodologia ere proposatzen du.

Tesiaren lehen helburuaren lorpena, hau da, kasu askotan aplika daitekeen simulazio-eredu bat garatzea, agerian geratzen da `FLBEIA` aplikatu den kasu guztiekin. Gainera, eredua erreferentea da gaur egun Europan: arrantza-kudeaketari aholkularitza emateko (ICES 2018b) eta Europako hainbat ikerketa-proiektutan erabiltzen ari da, eta nazioarteko hainbat ikastaro eman ditugu mundu osoko ikasleekin. Gainera, kanpoko arrantza-zientzialariekin elkarlanean ari gara, `FLBEIA`-ren gaitasunak are gehiago handitzeko. Bereziki, Norvegiako itsas ikerketako institutuarekin, IMR-rekin, elkarlanean ari gara `FLBEIA` espezie anitzdun Gadget ereduaz lotzeko. Loturak `FLBEIA`-n tamaina egitura eta interakzio trofikoak txertatuko ditu, eta `FLBEIA` konplexutasun ertaineko ekosistema-ereduen artean posizio nabarmena izatea eragingo du. Bigarren helburua simulazio-ereduak balioztatzeko prozesuarekin lotuta dago, eta arrantza-kudeaketako simulazio-ereduetan GSA tekniken aplikazioa sustatzean datza. Helburua lortzeko, irizpide berriak zehaztu dira literatura zientifikoan gehien erabiltzen diren bi metodoetarako, eta bi metodo horiek simulazio-eredu konplexuetan aplikatzea errazteko jarraibideak ere proposatu dira. Jarraibideak ziurgabetasunaren parametrizazioan eta sarrera-faktoreen kopurua murriztean, dimentsionaltasunaren madarikazioari aurre egiteko, zentratuta daude .

Hipotesiei dagokienez, hirurak GSA eta `FLBEIA` metodoen konbinazioarekin berretsi ziren. Lehenik, arrantzarako simulazio-ereduetan orokorrean ziurgabetzat jotzen diren sarrera-faktoreetako batzuk sailkapenaren behealdean zeuden. Bigarrenik, hemen zehaztutako hautaketa-irizpideak literaturan aurkitutako beste bi irizpideak gainditu zituen (irteera-aldagai bakoitzerako sarrera-faktore kopuru finko bat hautatzen duen irizpidea eta Savageren puntuazioetan oinarritutako irizpidea). Hirugarrenik, hemen definitutako konbergentzia-irizpidearen kostu konputazionala Sarrazin et al. (2016)-ek proposatutakoa baino baxuagoa zela aurkitu zen. Gainera, beste bi ondorio garrantzitsu lortu ziren. Lehenik eta behin, arrantza-kudeaketako simulazio-ereduetan sentikortasun analisi lokalak baliogabetzea, irteera-aldagai gehienen aldakuntza sarrera-faktoreen arteko korrelazioak eragin zuelako. Eta bigarrenik, MSE eta GSA metodologiak konbinatzeak izan dezakeen erabilgarritasuna stocken ebaluketarako eredu zehatzen beharrik ez duten stockak identifikatzeko.

Amaitzeko, hainbat ikerketa lerro proposatzen dira, arrantza-kudeaketaren simulazio-ereduen kalitatea nabarmen hobetuko dutenak, eta, beraz, arrantza-kudeaketa bera ere: metamodeloen garapena sentsibilitate-indizeen kalkulua sustatzeko eta kudeaketa-estrategien ebaluazioa denbora errealean burutzeko, oreka ekonomikoko ereduen integrazioa `FLBEIA`-n, arrantza-kudeaketaren sinplifikazioa GSA eta MSE metodologiak konbinatuz, arrantza-simulazioko ereduen ziurgabetasunaren parametrizazioa eta flotaren dinamika-ereduen hobekuntza.

Resumen

Esta tesis nace de la necesidad de desarrollar modelos integrados de simulación bioeconómica identificada por el comité científico, técnico y económico de pesca de la Comisión Europea. El marco de aplicación del modelo debía ser la evaluación de impacto de las estrategias de gestión de pesca. Además, el modelo desarrollado debía de ser lo suficientemente genérico y general como para aplicarse en una amplia gama de estrategias de gestión pesquera y debía seguir el enfoque de evaluación de estrategias de gestión (management strategy evaluation, MSE, en sus siglas en inglés) (Punt et al. 2016).

Los modelos de simulación de sistemas naturales son abstracciones de la realidad y no son capaces de describir el sistema real de manera perfecta. Por lo que es necesario que el modelo represente el sistema modelado de forma tan precisa como sea necesario según el propósito preestablecido (Rykiel 1996). El proceso de evaluar la idoneidad de los modelos se conoce como validación. Sin embargo, no existe un procedimiento que garantice categóricamente que un modelo dado es válido. La validación, es un proceso que tiene lugar a lo largo de todo el proceso de desarrollo de un modelo (Sargent 2011). El análisis de sensibilidad global (global sensitivity analysis, GSA, en sus siglas en inglés) es una técnica cuantitativa que se utiliza para avanzar en la validación de los modelos de simulación (ver Norton (2015), Plischke (2016) o Pianosi et al. (2016) para revisiones recientes en este campo). La técnica consiste en caracterizar la variabilidad en los resultados que ofrece el modelo en función de la variabilidad en los factores de entrada.

Para satisfacer la demanda de un modelo de simulación bioeconómica, desarrollamos FLBEIA (Bio-Economic Impact Assessment in `FLR`). Teniendo en cuenta la importancia de la validación en el desarrollo de modelos de simulación, esta tesis tiene dos objetivos: primero, desarrollar FLBEIA, un modelo de simulación multi-

stock y multiflota [2] genérico que sigue el enfoque MSE, y segundo, avanzar en su validación usando GSA, mientras se promueve el uso de esta metodología en modelos de simulación de pesquerías.

En relación con la aplicación de modelos de simulación de gestión pesquera y métodos de GSA, esta tesis plantea tres hipótesis:

- Los factores de entrada que generalmente se consideran inciertos, no siempre son los más importantes en téminos de la variabilidad total.
- Los criterios de convergencia definidos para los métodos cuantitativos de GSA no cubren todas las situaciones en las que se aplican estos métodos.
- La selección de los factores de entrada mas importantes en la aplicación de métodos de cribado en modelos con datos de sálida multidimensionales está sesgada.

En la introducción, para familiarizar al lector con el contenido de la tesis, hacemos una revisión sobre sus cuatro pilares: gestión pesquera, MSE, validación de modelos y GSA. La revisión bibliográfica realizada sobre gestión pesquera ha motivado el artículo científico titulado: *"Contribution of mathematics to fisheries management throughout history"*. El artículo está en preparación y se enviará a la revista *"Fish and Fisheries"*.

Después de la introducción, el Capítulo 2 proporciona una descripción detallada del modelo `FLBEIA`, presentando cómo se ha codificado internamente y las ecuaciones utilizadas para describir cada uno de los procesos que constituyen el modelo. El modelo se ha codificado usando el software estadístico `R`, los paquetes `FLR`, y se distribuye como un paquete del mismo software. En el momento de comenzar el desarrollo del modelo, la mayoría de los modelos existentes describían exlusivamente el componente biológico del sistema pesquero o teían un componente económico muy simple, o al revés. Por lo tanto, `FLBEIA` fue concebido para equilibrar estas dos componentes del sistema pesquero bajo un marco de MSE. `FLBEIA` puede clasificarse como un "modelo de complejidad intermedia para evaluación de ecosistemas" (Plagányi et al. 2014) que se enfoca en la gestión de la actividad pesquera en un contexto de pesquerías mixtas. Se ha publicado una descripción del modelo en la revista científica *SoftwareX*: *"`FLBEIA`: A simulation model to conduct bio-economic evaluation of fisheries management strategies"*, (Garcia et al. 2017b).

En la segunda parte de la tesis, nos centramos en la validación del modelo y elegimos la metodología de GSA para avanzar en el proceso de generar confianza en

[2] *stock* se refiere a una unidad de gestión de una población de peces y *flota* a un grupo de buques que comparten similares características técnicas

`FLBEIA`. Como el método de descomposición de la varianza de Sobol es considerado el método de referencia por muchos autores (Homma and Saltelli 1996, Sarrazin et al. 2016), inicialmente, pensamos en usar exclusivamente el método de Sobol para aplicar el GSA. Sin embargo, su alto costo computacional nos hizo considerar otras alternativas. Siguiendo las recomendaciones en la literatura (Confalonieri et al. 2010, Saltelli et al. 2008), decidimos combinar el método de Sobol con el método de cribado de Morris para reducir el número de factores de entrada. Al combinar ambos métodos, nos enfrentamos con el problema de garantizar que esta combinación se realizara de manera robusta. Es decir, garantizar que los factores de entrada seleccionados fueran realmente los más importantes.

La selección de los factores de entrada más importantes en el método de Morris se realiza visualmente, seleccionando aquellos que se diferencian del resto en el *valor absoluto del efecto elemental medio* (Campolongo et al. 2007). En los modelos con salida multidimensional, la selección se realiza para cada una de las variables de salida del modelo, y el conjunto de factores de entrada seleccionados para cada una de las variables se fusionan en un solo conjunto. El problema reside en que, si hay muchas variables de salida, es difícil mantener inalterada la selección visual. Además, la selección visual no se puede utilizar en métodos de simulación como el bootstrap. Para superar este problema, desarrollamos un nuevo criterio de selección que se basa en los tres aspectos que se tienen en cuenta al realizar la selección visual: el número de factores de entrada seleccionados, el v*alor absoluto del efecto elemental medio* en relación con su valor máximo, y la diferencia en los *valores absolutos de los efectos elementales medios* de factores consecutivos. Por otro lado, los criterios de convergencia existentes para los métodos de GSA se centran en el valor de los índices de sensibilidad, su clasificación o la convergencia de los índices en la parte inferior de la clasificación (Sarrazin et al. 2016). Sin embargo, en nuestro caso el objetivo en la aplicación del método de Morris en esta tesis era identificar los factores de entrada en la parte superior de la clasificación, sin importar su posición o valor exacto. Como los objetivos en Sarrazin et al. (2016) son más exigentes, el uso de los criterios de convergencia asociados podría generar un recargo computacional. Por lo tanto, definimos un nuevo criterio de convergencia diseñado específicamente para el objetivo establecido. Los dos nuevos criterios propuestos en esta tesis, es decir los criterios de selección y convergencia, se describen en el Capítulo 3 y su descripción junto con la evaluación de su funcionamiento se ha publicado en la revista científica *Environmental Modeling & Software*: *"Robust combination of the Morris and Sobol methods in complex multidimensional models"*, (Garcia et al. 2019a).

La aplicación de la metodología desarrollada comienza en el Capítulo 4. En este capítulo, presentamos la aplicación de `FLBEIA` a la pesquería demersal que opera alrededor de la fachada atlántica de la península Ibérica. En esta aplicación, comparamos el rendimiento bioeconómico del sistema pesquero bajo dos políticas de gestión diferentes: la política de obligación de desembarque (i.e la prohibición de descartar los peces) introducida en la última reforma de la política pesquera común europea, y la política anterior en la que el pescado capturado podía descartarse (arrojarse al mar). Además, definimos nuevos puntos de referencia para gestionar la pesquería, y probamos si podrían usarse para reducir el presumible efecto negativo de la nueva política. Como resultado se obtuvo que el impacto de la obligación de desembarco dependía del periodo de tiempo, de la flota y que estaba muy influenciado por los supuestos sobre la dinámica de la misma. A nivel global, los nuevos puntos de referencia mitigaron la disminución de los beneficios generados por la implementación de la obligación de desembarque. Sin embargo a nivel de flota los resultados variaban. El contenido de este capítulo ha sido publicado en la revista científica *ICES journal of Marine Science*: *"Bio-economic multi-stock reference points as a tool for overcoming the drawbacks of the landing obligation"*, (Garcia et al. 2017a).

En el Capítulo 5, se probaron los criterios y las directrices propuestos en el Capítulo 3, en la implementación de `FLBEIA` presentada en el Capítulo 4. Siguiendo las directrices del Capítulo 3, el modelo fue condicionado de tal manera que se redujo el número efectivo de factores de entrada en un 90%. La incertidumbre en los factores de entrada se condicionó utilizando el valor medio utilizado en el Capítulo 4 y un coeficiente de variación del 30%. Los criterios de selección y convergencia definidos en el Capítulo 3 se aplicaron a los *valores absolutos de los efectos elementales medios* de Morris sobre 37 variables de salida. El método de Sobol se aplicó después considerando solamente los factores de entrada seleccionados por el método de Morris. La varianza de la mayoría de las variables de salida se debía a la interacción entre los factores de entrada. Además, los resultados eran dependientes del stock y de la flota. La descomposición de la varianza global se estimó utilizando el método propuesto por Lamboni et al. (2011). En general, los factores de entrada que tenían un mayor impacto en los resultados fueron los relacionados con la dinámica a corto plazo de las flotas (cuánto esfuerzo pesquero se ejerce y como se distribuye), la mortalidad natural y el peso de los stocks de peces. Por el contrario, los factores de entrada directamente relacionados con el reclutamiento de los stocks (que son aquellos en los que la literatura más se centra en términos de incertidumbre) se encontraban en la parte inferior de la clasificación. Los factores de entrada relacionados con los errores cometidos en el proceso de gestión del sistema, cuya variación se puede reducir a través de la investigación, se encontraban en la parte superior de la clasificación únicamente para los stocks objetivo de la pesquería. En el momento de finalizar la redacción de esta tesis, estamos escribiendo un artículo destacando el potencial de combinar las metodologías de GSA y de MSE, y mostrando los resultados obtenidos en la combinación de ambos análisis. El artículo se enviará a la revista científica *Methods in Ecology and Evolution*: *"Potential of applying global sensitivity analysis to fisheries management simulation models"*.

En el Capítulo 6, presentamos las herramientas desarrolladas en el marco de la tesis que están disponibles gratuitamente. El contenido del capítulo es puramente técnico y contribuye a la transferencia de conocimiento, facilitando el uso de `FLBEIA` y de los criterios desarrollados en esta tesis. Si bien la estructura y las fórmulas utilizadas para construir `FLBEIA` y definir los criterios de selección y convergencia se explican en los Capítulos 2 y 3, en este capítulo mostramos cómo usarlos en la práctica. Como complemento del paquete `FLBEIA`, también hemos desarrollado una aplicación Shiny para facilitar el análisis de los resultados. En este capítulo, mostramos cómo usarlo. Finalmente, se han incroporado todos los resultados obtenidos en la aplicación de los métodos de Morris y Sobol en una aplicación Shiny que facilitó enormemente la identificación de patrones en los índices de sensibilidad.

Los modelos de simulación multistock y multiflota de gestión de pesquerías permiten anticipar el impacto de las estrategias de gestión en los sistemas pesqueros. Como tal, proporcionan una base científica para apoyar el proceso de toma de decisiones integrando en el mismo marco las dimensiones biológica, económica y social del sistema pesquero. Antes, las decisiones de gestión se basaban principalmente en consideraciones biológicas. Sin embargo, impulsados por la gestión de la pesca basada en el ecosistema (Pikitch et al. 2004), la incorporación de las dimensiones económica y social se ha vuelto indispensable. Por lo tanto, los modelos del tipo de `FLBEIA` se han convertido en una valiosa herramienta para apoyar las decisiones de gestión. Uno de los principales problemas en el uso de estos modelos es la gran incertidumbre que existe en la modelización matemática de los sistemas de pesca. La incertidumbre proviene de ambos, la variabilidad natural en el sistema y el error en su observación. La aproximación MSE proporciona el marco para incorporar todas estas incertidumbres en el proceso de toma de decisiones. A su vez, el GSA permite caracterizar el impacto de la incertidumbre en el funcionamiento de los modelos.

Sin embargo, las metodologías de GSA y MSE rara vez se combinan en modelos de simulación de gestión pesquera. Por lo tanto, esta tesis no solo proporciona una herramienta para apoyar el proceso de toma de decisiones en la gestión pesquera, sino también una metodología para mejorar la forma en que se utilizan los modelos de simulación pesquera en la práctica.

La consecución del primer objetivo de la tesis, el desarrollo de un modelo de simulación que se pueda aplicar ampliamente, se evidencia por la gran cantidad de casos de estudio en los que se ha aplicado `FLBEIA`. Además, el modelo es hoy en día un referente en Europa: se está utilizando para proporcionar asesoramiento sobre gestión pesquera (ICES 2018b), en varios proyectos europeos de investigación y hemos impartido varios cursos internacionales con estudiantes de todo el mundo. Además, estamos colaborando con científicos pesqueros externos para aumentar aún más las capacidades de `FLBEIA`. En particular, estamos colaborando con el instituto de investigación marina (IMR) en Noruega para vincular `FLBEIA` con el modelo múltiespecies Gadget. El enlace permitirá incorporar la estructura por talla e interacciones tróficas a `FLBEIA` y hará que `FLBEIA` ocupe una posición destacada entre los modelos de ecosistema de complejidad intermedia. El segundo objetivo, se relaciona con el proceso de validación de los modelos de simulación y consiste en promover la aplicación de técnicas de GSA en los modelos de simulación de gestión pesquera. El objetivo se ha logrado definiendo nuevos criterios para combinar dos de los métodos de GSA más populares en la literatura científica, y un conjunto de directrices para facilitar la aplicación de estos métodos en modelos de simulación complejos. Las directrices se centraron principalmente en el condicionamiento de la incertidumbre y en la reducción del número efectivo de factores de entrada para combatir la maldición de la dimensionalidad.

En cuanto a las hipótesis, las tres fueron corroboradas con la combinación de los métodos de GSA y `FLBEIA`. De la tesis se deduce que algunos de los factores de entrada generalmente considerados inciertos en los modelos de simulación de pesquerías estaban en la parte inferior de la clasificación. También se obtiene que el criterio de selección definido aquí superó a los otros dos criterios encontrados en la literatura (el criterio que selecciona un número fijo de factores de entrada para cada variable de salida y el criterio basado en las puntuaciones de Savage). Finalmente, se encontró que el coste computacional del criterio de convergencia definido aquí era más bajo que el propuesto por Sarrazin et al. (2016). Además, se obtuvieron otras dos conclusiones relevantes. Primera, la invalidación del análisis de sensibilidad local en los modelos de simulaciones de gestión pesquera debido a que la variación de la mayoría de las variables de salida estaba motivada por la interacción entre los factores de entrada. Segunda, la potencial utilidad de la combinación de las metodologías de MSE y GSA para identificar los stocks para los cuales podría ser innecesario implementar modelos precisos de evaluación de stocks.

Al final de la tesis se proponen varias líneas de investigación que mejorarán considerablemente la calidad de los modelos de simulación de gestión pesquera y por ende la misma gestión pesquera: el desarrollo de metamodelos para promover el cálculo de índices de sensibilidad y la evaluación en tiempo real de estrategias de gestión, la integración de modelos de equilibrio económico en `FLBEIA`, la simplificación de la gestión de la pesca mediante la combinación de las metodologías de GSA y MSE, el condicionamiento de la incertidumbre en los modelos de simulación pesquera y la mejora de los modelos de dinámica de flota existentes.

Summary

This thesis was motivated by the need of developing integrated bio-economic simulation models identified by the scientific, technical and economic committee for fisheries of the European Commission. The model should be appropriate to carry out impact assessment of management strategies on fisheries. Moreover, it should be general enough to be applicable to a wide variety of fisheries and management strategies and should follow the management strategy evaluation (MSE) approach (Punt et al. 2016).

Mathematical models of natural systems are abstractions of reality and can never describe the real system perfectly. Instead, what is needed is that the model represent the modelled system well enough for the stated purpose (Rykiel 1996). The process of evaluating the adequacy of a model is called validation. However, there is no procedure that can be used to ensure categorically that a given model is valid. Instead, validation is a process that takes place throughout the whole of the development process of the model (Sargent 2011). Global Sensitivity Analysis (GSA) is one of the quantitative techniques that can be used for such a validation (see Norton (2015), Plischke (2016) or Pianosi et al. (2016) for recent reviews on the field). It consists in characterising the variability in the model output as a function of the variability in the input factors.

To satisfy the demand for a bio-economic simulation model, we developed `FLBEIA` (Bio-Economic Impact Assessment in `FLR`). Considering the importance of validation in the development of simulation models, this thesis has two objectives: first, to develop `FLBEIA`, a generic multi-stock and multi-fleet model [3] that follows the MSE approach, and second, to advance its validation using GSA, while promoting the use

[3] *Stock* refers to a management unit of a fish population and *fleet* to a group of vessels that share similar technical characteristics.

of GSA in fisheries simulation models.

Furthermore, in relation with the application of fisheries management simulation models and GSA methods this thesis raises three hypotheses:

- The input factors that are usually considered uncertain are not always the most important.
- The convergence criteria defined for quantitative GSA methods do not cover all situations where GSA is applied.
- The selection of important input factors in the application of screening methods in multi-dimensional output models is biased.

In the Introduction, to familiarise the reader with the contents of the thesis, we provide a background for its four pillars: fisheries management, MSE, model validation and GSA. The review conducted of fisheries management has motivated a scientific article titled: *"Contribution of mathematics to fisheries management throughout history"*. That article is in preparation and will be sent to the journal *"Fish and Fisheries"*.

After the Introduction, Chapter 2 provides a detailed description of the `FLBEIA` model, presenting how it has been coded internally and the equations used to describe each of the processes that build up the model. `FLBEIA` has been coded in the R language, it uses the `FLR` packages and it is distributed as an R library. At the time of starting the development of the model, most of the existing models were biologically oriented with a very simple economic component, or the other way around. Hence, `FLBEIA` was conceived to balance those two dimensions of the fishery system within an MSE framework. `FLBEIA` can be categorised as a 'model of intermediate complexity for ecosystem assessments' (Plagányi et al. 2014) which is focused on the management of fishing activity in the context of mixed fisheries. A description of the model has been published in the scientific journal *SoftwareX*: *"`FLBEIA`: A simulation model to conduct bio-economic evaluation of fisheries management strategies"*, (Garcia et al. 2017b).

In the second part of the thesis, we focused on the validation of the model and chose GSA to make progress in the process of building trust in `FLBEIA`. As the Sobol variance decomposition method is considered the reference method by many authors (Homma and Saltelli 1996, Sarrazin et al. 2016), we initially planned to use exclusively the Sobol method to apply GSA. However, its high computational cost made us consider other alternatives. Following the recommendations in the literature (Confalonieri et al. 2010, Saltelli et al. 2008), we decided to combine the Sobol method with the Morris screening method to reduce the number of input factors. When combining both methods we were faced with the problem of ensuring that it was being done robustly, that is, ensuring that the selected input factors were really the most important ones.

On the one hand, the selection of the most important input factors in the Morris method is done visually: selecting those that are distinguished from the rest in the value of the *mean absolute elementary effect* (Campolongo et al. 2007). In multi-dimensional output models, the selection is done for each of the output variables of the model, and the set of input factors selected for each of the variables are merged into a single set. However, if there are many output variables, it is difficult to maintain the visual selection unaltered. Furthermore, the visual selection cannot be used in simulation approaches like bootstrap. To overcome this problem, we developed a new selection criterion that is based on the three aspects that are taken into account when carrying out the visual selection: the number of input factors being selected, the value of the *mean absolute elementary effect* relative to their maximum value, and the difference in the *mean absolute elementary effects* of consecutive factors. On the other hand, the existing convergence criteria for GSA methods were focused on the value of the sensitivity indices, their ranking, or the convergence of the indices in the lower part of the ranking (Sarrazin et al. 2016). However, the objective in the application of the Morris method in this thesis was different, namely, to identify the input factors in the top of the ranking, no matter their exact position or value. As the objectives in Sarrazin et al. (2016) are more demanding, using the associated convergence criteria could lead to a computational surcharge. Hence, we defined a new convergence criterion specifically designed for the stated objective. The two new criteria proposed in this thesis, namely the selection and the convergence criteria, are presented in Chapter 3 and their description together with the evaluation of their performance have been published in the scientific journal *Environmental Modelling & Software*: *"Robust combination of the Morris and Sobol methods in complex multidimensional models"*, (Garcia et al. 2019a).

The application of the developed method starts in Chapter 4. In that chapter, we present the application of `FLBEIA` to the demersal fishery that operates around the Atlantic part of the Iberian Peninsula. In this application, we compared the bio-economic performance of the fishery system under two different management policies: the landing obligation policy (a fish discard ban) introduced in the last reform of the European common fisheries policy, and the previous policy where the fish caught could be discarded (i.e. thrown back into the sea). Furthermore, we defined new reference points to manage the fishery, and tested whether they could be used to cushion the negative effect of the new policy. We found that the impact of the landing obligation was time and fleet dependent and highly influenced by the assumptions about fleet dynamics. At the fishery level, the new reference points mitigated the decrease in profits generated by the implementation of the landing obligation. However, at the fleet level, the effect depended on the fleet and the time period considered. The content in this chapter has been published in the scientific journal *ICES journal of Marine Science*: *"Bio-economic multi-stock reference points as a tool for overcoming the drawbacks of the landing obligation"*, (Garcia et al. 2017a).

Chapter 5 presents the results of testing the criteria and guidelines proposed in Chapter 3 with the `FLBEIA` implementation presented in Chapter 4. Following the guidelines in Chapter 3, the model was conditioned in such a way that the effective number of input factors was reduced by 90%. The uncertainty in the input factors was conditioned using the mean value used in Chapter 4 and a coefficient of variation of 30%. The selection and convergence criteria defined in Chapter 3 were applied to the Morris *mean absolute elementary effects* over 37 output variables. The Sobol method was applied afterwards, considering only the input factors selected by the Morris method. The variance of most of the output variables was driven by the interaction between input factors. Moreover, the results were stock and fleet dependent. The decomposition of the overall variance was estimated using the method proposed by Lamboni et al. (2011). Overall, the input factors that had the biggest impact on the results were those related with the short-term dynamics of the fleets (how much fishing effort to exert and how to distribute it), and the natural mortality and weight of the fish stocks. Oppositely, the input factors directly related with stock-recruitment (which are the ones the literature most focuses on in terms of uncertainty) were in the lower part of the ranking. The input factors related with the errors committed in the management process of the system, whose variance can be reduced through further research, were in the upper part of the ranking only for the stocks targeted by the fishery. At the time of finalising the writing of this thesis, we are writing an article highlighting the potential of combining GSA and MSE, and presenting the findings obtained in the combination of both approaches. The article will be sent to the scientific journal *Methods in Ecology and Evolution* and titled *"Potential of applying global sensitivity analysis to fisheries management simulation models"*.

In Chapter 6, we present the computational tools developed in the framework of the thesis that are freely available. The content of the chapter is purely technical and contributes to the transfer of knowledge, facilitating the use of `FLBEIA` and the criteria developed in this thesis. While the structure and formulas used to build up `FLBEIA` and define the selection and convergence criteria are explained in Chapters 2 and 3, in this chapter we show how to use them in practice. As a complement to the `FLBEIA` package, we have also developed a Shiny application to facilitate the analysis of the results, and in this chapter, we show how to use it. Finally, we have placed all the results obtained in the application of the Morris and Sobol methods in a Shiny application which facilitated enormously the identification of patterns in the sensitivity indices.

Multi-stock and multi-fleet fisheries management simulation models allow anticipating the impact of management strategies in fishery systems. As such, they provide a scientific basis for a decision making process integrating the biological, economic and social dimensions of the fishery system in the same framework. In the past, management decisions were mainly based on biological considerations. However, encouraged by the ecosystem-based fishery management (Pikitch et al. 2004), the incorporation of economic and social aspects has become indispensable. Thus, `FLBEIA`-like models have become a valuable tool to support management decisions. One of the main problems in the use of these models is the great uncertainty that exists in the mathematical modelisation of fishery systems. The uncertainty comes from both the natural variability in the system and the errors in its observation. MSE provides a framework to incorporate all these uncertainties in the decision making process. In turn, GSA allows characterising the impact of the uncertainty on the performance of the models. However, GSA and MSE are rarely combined in fishery management simulation models. Thus, this thesis not only provides a tool to support the decision making process in fisheries management but also a set of guidelines to improve how fishery simulation models are used.

The achievement of the first objective of the thesis, the development of a simulation model that can be applied widely, is evidenced by the large number of case studies in which `FLBEIA` has been applied. Moreover, the model is nowadays a reference in Europe: it is being used to provide fisheries management advice (ICES 2018b), by several European research projects, and we have taught several international courses with students around the world. Additionally, we are collaborating with external fisheries scientists to further increase `FLBEIA`'s capabilities. In particular, we are collaborating with the Institute of Marine Research (IMR) in Norway to link `FLBEIA` with the Gadget multi-species model. The link will make it possible to incorporate length structure and trophic interactions into `FLBEIA` and will make FLBEIA occupy a prominent position among ecosystem models of intermediate complexity. The second objective relates with the process of validating simulation models and consists in promoting the application of GSA techniques to fishery management simulation models. The objective has been achieved, defining new criteria to combine two of the most popular GSA methods in the scientific literature, and a set of guidelines to facilitate the application of these methods in complex simulation models. The guidelines were mostly focused on the conditioning of the uncertainty and principally on the reduction of the effective number of input factors to fight the curse of dimensionality.

Regarding the hypotheses, the three were corroborated with the combination of GSA and FLBEIA. First, some of the input factors usually considered uncertain in fisheries simulation models were in the lower part of the ranking. Second, the selection criterion defined here outperformed the other two criteria found in the literature (the criterion that selects a fixed number of input factors per output variable and the criterion based on Savage scores). Third, the computational cost of the convergence criterion defined here was found to be lower than that proposed by Sarrazin et al. (2016). Additionally, another two relevant conclusions were obtained. First, local sensitivity analysis in fishery management simulations models was found to be invalid because the variance of most of the output variables was driven by the interaction between input factors. And second, the combination of the MSE approach and GSA was found to be useful for identifying those stocks for which implementing accurate stock assessment models could be unnecessary.

Finally, several research lines that will considerably improve the quality of fisheries management simulation models, and fisheries management itself, are proposed: the development of metamodels to promote the calculation of sensitivity indices and the real-time evaluation of management strategies, the integration of economic equilibrium models in FLBEIA, the simplification of fisheries management by combining GSA with MSE, the uncertainty conditioning of fisheries simulation models and the improvement of existing models of fleet dynamics.

Chapter 1

Introduction

The historical review conducted on fisheries management has motivated the scientific article titled: "Contribution of mathematics to fisheries management throughout history". The article is under preparation and will be sent to the journal ***"Fish and Fisheries"****.*

1.1 Introduction

In this chapter we conduct a historical revision of the main fields covered in this thesis. We start with a revison of fisheries science, focused on the development of mathematical models over years. Then, we explain how fisheries management is implemented nowadays in practice. The model we have developed in this thesis, `FLBEIA`, has been build following the management strategy evaluation approach (Punt et al. 2016). Hence, the historical development of this modelling approach is also presented in this chapter. The use of simulation models provide a perfect framework to test different aspects of fisheries management. However, as models are simplifications of the system they represent, it is necessary to validate them and prove they are good enough for the intended purpose (Rykiel 1996). Therefore, in Section 1.3, we move from fisheries management to the validation of mathematical models. We review the application of validation techniques since its emergence around 1950. Then, we focus on global sensitivity analysis (GSA) (Saltelli et al. 2008), the methodology used and further developed as part of this thesis to validate `FLBEIA`. In the next two sections we explain the motivation and the objectives of the thesis. Finally, as this thesis has emerged as a result of the work carried out in AZTI technological center, in the last part of the introduction we briefly present the work carried out by this center in relation with fisheries management.

1.2 Mathematical modelling in fisheries management

1.2.1 The evolution of mathematical models in fisheries management

At the beginning, fisheries science was exclusively concerned with the dynamics and the sustainability of exploited fish stocks. However, it has became a multi-disciplinary research field that embraces the study of biological, economic and social dimensions of the fishery systems. Fisheries science is a relatively modern science where the first steps took place in the second half of the 19th century (Pauly 1993). The ultimate objective of fisheries science is to inform managers about the biological, economic and social impact of alternative options to manage fisheries, based on scientifically sound analysis. In turn, some of the main objectives of fisheries management are: to ensure the sustainability of fisheries resources while promoting an economically efficient fishing sector, protecting local communities, and covering the demand of fish protein. In this section, we will summarize the history of fisheries management, with the focus on the evolution of mathematical modelling. Figure 1.1 shows some of the most important events as regards to the evolution of mathematical modelling in fisheries management in chronological order.

In 1854 Cleghorn was the first in introducing the idea of overfishing, concerned about the fluctuations in English herring fishery (Cleghorn 1854) . However, at that time it was a general believe that the oceans were so vast that fishing practices of the time were unable to impact negatively on fish stocks. The zoologist Huxley, in the inaugural presentation of the International Fisheries Exhibition in 1883 (Finley (2009), https://mathcs.clarku.edu/huxley/SM5/fish.html), said in relation to the fishing technologies of the moment that "... the cod fishery, the herring fishery, the pilchard fishery, the mackerel fishery, and probably all the great sea fisheries, are inexhaustible; that is to say, that nothing we do seriously affects the number of the fish. And any attempt to regulate these fisheries seems consequently, from the nature of the case, to be useless." Unfortunately, in less than a century, the reality proved otherwise. Although, it is also true, that the efficiency of fishing gears improved greatly over the years. Hence, the fishing technologies of the second part of the 20th century had nothing to do with those which Huxley was referring to. Before the end of the 19th century, the decrease of fish abundance in several fishing

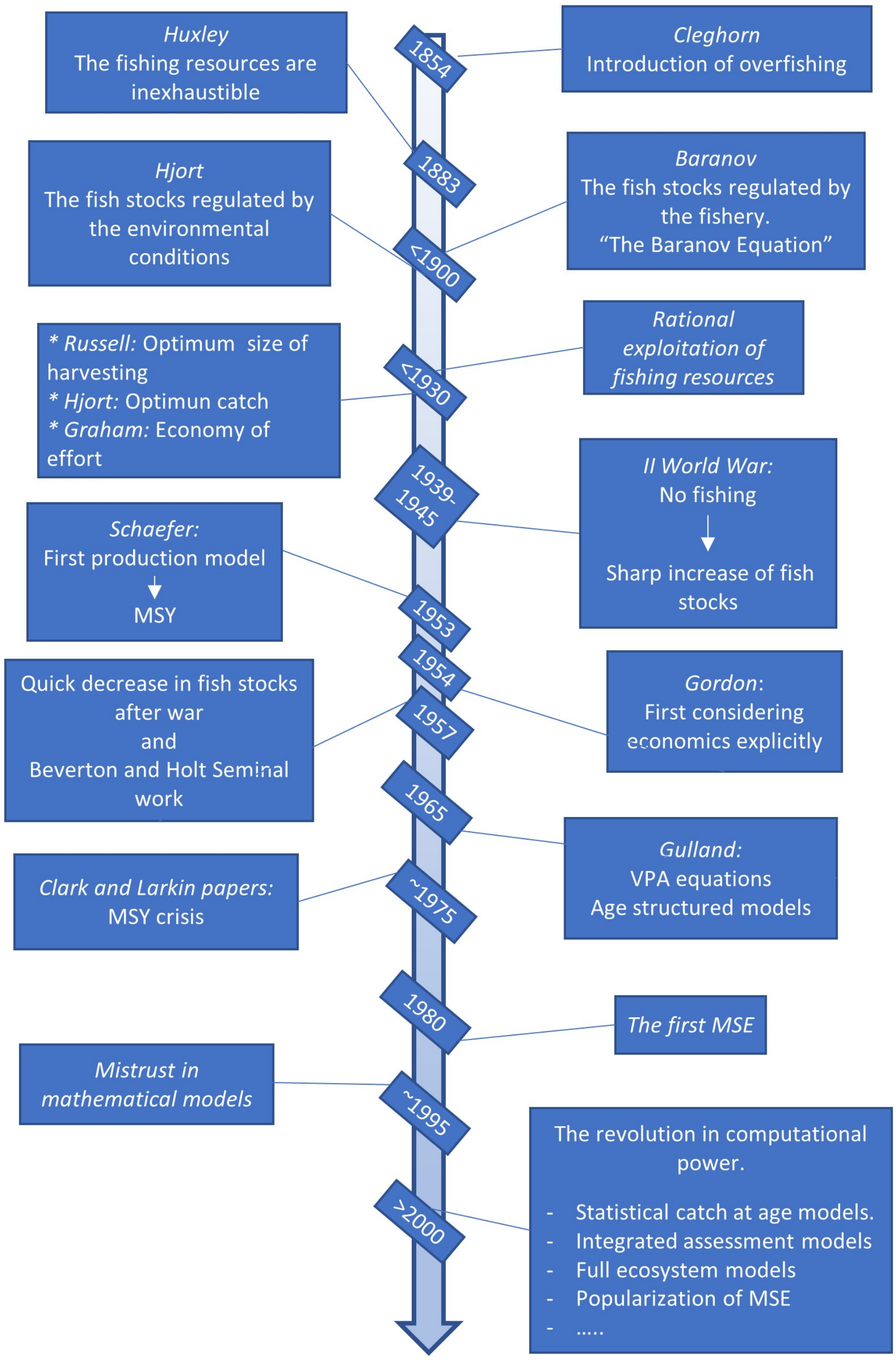

Figure 1.1: Historical evolution of fisheries science focused on the evolution of mathematical modelling.

grounds begin to raise voices against the thought of inexhaustibility of fish stocks (Sims and Southward 2006).

At the beginning of the 20th century, fishery science was divided into two different branches (Pauly 1993). In one of them, which main exponent was the Russian Baranov, the scientists thought that the fish stocks were regulated by the fishery. In the other one, represented by the Norwegian Hjort, they thought that the environmental conditions were the main drivers of the fish abundance. Baranov in 1918, was the first in combining growth and abundance to develop a catch equation (Larkin 1977). Based on this equation, he laid the foundations of quantitative fisheries science. Nowadays, it is still one of the most important equations in fisheries modelling. The 1930s were the years of the rational exploitation of fishing resources. Russel was the first in dealing with this issue (Russell 1932). He concluded that it was impossible to stabilize a fishery in a level that could yield a constant maximum level of catch annually. The solution was to predict the stock level in advance to predict the time varying optimum level of catch. Besides, he introduced the question of the best size to start harvesting a stock. In 1933, Horjt introduced the concept of optimum catch, which evolved afterwards to maximum sustainable yield (MSY) (Rosenberg et al. 1993). In 1935, Graham introduced the concept of the 'economy of effort' and the optimum age to harvest. He was concerned about the idea that fishers were wasting fishing effort by exerting fishing levels that ultimately were leading to a decrease in catch.

The II World War was an unintentional and valuable experiment in fisheries science. The fishing activity in the North Sea stopped during the war years (1939-1945) which produced a great increase in the abundance of fish populations. The quick decrease in the abundance, once the fishing activity was re-established, motivated the seminal work of Beverton and Holt (Beverton 1957). Basically, they recompiled and further developed the existing knowledge. They structured the work around what they call the "four primary factors": recruitment[1] , natural mortality, fishing mortality and growth. Furthermore, they applied the models they revised to the North Sea data. In the same decade, Schaefer was the first author in proposing a surplus-production model to estimate the biomass of a fish population over time (Schaefer 1954). This model had the advantage of providing an analytical solution for the estimation of MSY. This fact increased enormously the popularity of MSY as reference point (Mace 2001). Still today, surplus production models are one of the most popular stock assessment models used in practice.

[1] *Recruitment* refers to the fishes that becomes accessible to the fishery anually

Fishing is an economic activity and many authors in the first half of the 20th century already acknowledged the importance of economy in fisheries management (Baranov 1925, Beverton 1953, Huntsman 1944). However, specific research in the field was not carried out until the second half of the century (Gordon 1954). Nowadays, the fisheries research in economy and biology is still quite separate from each other. In general, the existing mathematical models are focused in biological or economic aspects of the system and tend to obviate or simplify the other (Garcia et al. 2017b). Gordon (1954) was the first author in considering fishery economics explicitly. He gave an analytical solution for the optimum intensity of fishing effort for a population in equilibrium. Clark, one of the most influential fishery economists, published in 1973 the paper "The economics of overexploitation" (Clark 1973). In the paper he suggested that MSY should be generally adopted at least as an upper limit and concluded that "The conservation of renewable resources would appear to require continual public surveillance and control of the physical yield and the condition of the stocks". Time has confirmed that he was right.

The popularity of MSY decreased in the 1970s. In 1977, Larkin forecasted it's dead in his paper "The epitaph of MSY", (Larkin 1977). Larkin argued that, MSY is associated to a high risk of recruitment failure because at MSY the most productive components of the populations have been reduced dramatically, it can not be attained simultaneously in mixed fisheries and it is not the best economic strategy. However, nowadays, it is the management objective of many fishery management agencies. Although, it is also true, that nowadays the objective is defined in terms of fishing mortality, instead of yield, and it comprises a broader definition than in the past (Rindorf et al. 2017). In fact, in 1992, the participants on the World Summit on Sustainable Development (`http://www.unmillenniumproject.org/documents/131302_wssd_report_reissued.pdf`), the European Commission among others, commit to bring depleted fish stocks to MSY no later than 2015. Nowadays, many fish stocks in Europe, and elsewhere, continue being below MSY. In consequence, one of the main objectives of the Europe's common fisheries policy (CFP) is to achieve MSY for all the stocks no later than 2020 (Salomon et al. 2014). One of the main criticism to MSY is that it is too high from an ecosystem functioning point of view (Larkin 1977, Mace 2001). As Clark already suggested in 1973 many authors consider that MSY should be a management limit and not an objective (Clark 1973, Mace 2001). However, from an economic perspective, when several fish stocks are exploited together, in the so called mixed fisheries, exceeding single stock MSY target could be more profitable than to stop fishing (Da Rocha et al. 2012, Garcia et al. 2017a). Also in the 70s, the equations of Virtual Population Analysis, the first generation of age structured stock assessment models, were formalized by Gulland (Angelini 2007).

As happened with MSY, the use of mathematical models had its own mistrust crisis at the end of the 20th century (Schnute and Richards 2001). This fact was motivated by the collapse of several fisheries. Holt himself, one of the promoters of mathematical modelling in fisheries science, recognized that an excessive weight had been placed on mathematics. The main problem in the application of mathematical models to manage fish stocks is the uncertainty that surrounds the system, from the data collection, through the choice of the correct assessment model, to the implementation of the management advice. Motivated by the problem with uncertainty, at the turn of the 20th century, a new approach to fisheries management emerged, the management strategy evaluation (MSE) approach (Punt et al. 2016). The ultimate objective of the approach is to identify management strategies that are robust to the uncertainty inherent in the fishery system. The new approach supposed a change of paradigm. Instead of looking for the model that best fitted to the data available, the objective is to find a management procedure which is robust to the uncertainty in the fishery system. The MSE approach was first used by the international whale commission (Punt and Donovan 2007) and it has been extended nowadays all around the world.

With the new century, the need of a more holistic approach to fisheries management, which takes into account ecosystem aspects, was identified, the so called Ecosystem Based Fisheries Management (EBFM) (Curtin and Prellezo 2010, Pikitch et al. 2004). The objective of EBFM is to ensure healthy marine ecosystems that are able to support sustainable fisheries. In order to support EBFM, end-to-end ecosystem models that considers target and non-target species and their predator-prey relationships were developed —(Christensen and Walters 2004, Fulton et al. 2011a, Shin and Cury 2004) . Furthermore, fishers are part of the ecosystem and their behaviour is considered a key factor in the success of management strategies (Fulton et al. 2011a). The MSE approach started being an approach focused exclusively on the stock. However, along the years and driven by the EBFM, more complex configurations arose and nowadays multi-stock and multi-fleet approaches are broadly applied (Garcia et al. 2017a, Marchal and Vermard 2013, Simons et al. 2015).

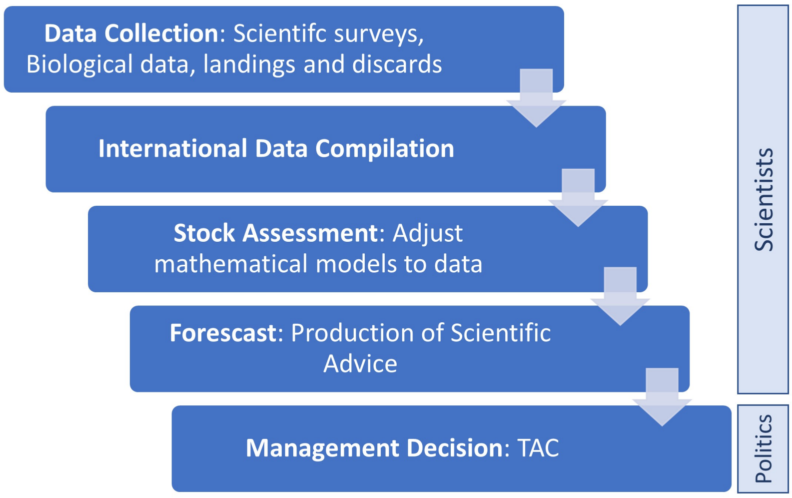

Figure 1.2: Steps taken annually to set the total allowable catch (TAC).

1.2.2 Fisheries management in practice

In Europe, fisheries management is operationalized through the CFP (Salomon et al. 2014), which establishes the overall objectives and rules of fisheries management in Europe. One of the main tools of the CFP is the total allowable catch (TAC) that is set annually for many of the exploited stocks in European waters. The principal steps taken in the process to set the TACs are shown in Figure 1.2. Usually, this process is conducted annually.

The first step in the provision of management advice is the sampling. Routinely the fisheries research institutes and the corresponding administrations collect the data relative to stock exploitation, biology and abundance. In Europe, the data collection is regulated through the data collection framework. The most basic data collected for each stock is the total landings. This data is normally recorded in logbooks [2] and communicated to research institutes by national administrations. Length distribution of landings is sampled at port by scientists for a number of trips selected randomly. Discards (the catches that are thrown into the sea), are sampled by observers on board commercial fishing vessels. Sampled trips represent a small proportion of total number of trips. Biological data, such as weight, fecundity and age at length are a sub-sample of the length distribution samples that are brought from the port to the laboratories to conduct the necessary analysis. Finally, for

[2] *Logbooks* store records of catch and effort registered at the time of the catch operation.

some stocks, there are scientific surveys at sea that are run periodically and which objective is to obtain relative or absolute abundance estimates of a certain fraction of the population (the recruitment or the spawning biomass for example). Sometimes there is alternative data available such as tagging or genetic data that provides additional information to the management advice provision process.

Fish stocks are usually shared by several countries and their management is conducted through international collaboration. The procedure used to merge the international data depends on the data available. In turn, the mathematical models used to assess the status of the stock depends on the data available, its quality and its informativeness. These models are mathematical models that are solved numerically to obtain estimates of abundance and exploitation levels over time. Undoubtedly, the most common assessment models are biomass dynamic and age structured assessment models. The estimates obtained from these models are then used to derive reference points for the stocks. The reference points are particular biomass and exploitation levels that are used to determine the stock status, i.e if it is being exploited sustainably, overexploited or overfished, and to generate the catch advice.

The management advice is generally produced using harvest control rules (HCRs). The HCRs are mathematical formulas used to generate the catch advice, commonly known as TAC, using the reference points, and current stock and exploitation levels. The HCRs can be divided in two groups depending on the type of data they used to generate the advice, model-based and model-free HCRs. Model-based HCRs used the output of an assessment model and reference points, and the model-free HCRs used time series of landings and or abundance indices. When there is not enough data to apply an assessment model or a model-free HCR the management advice is normally based on expert opinion and precautionary principles.

The implementation of the scientific management advice depends on several factors. On the one hand, the managers set the TAC based not only on the scientific advice but also on political considerations. On the other hand, the fishers will comply with the TAC depending on different factors, such as, the existing control and enforcement, or the economic incentives.

The whole process of generating and implementing the management advice is subject to a great uncertainty (Francis and Shotton 1997), from the typical sampling and measurement error in the data collection step, to the uncertainty in the implementation of the scientific advice. MSE emerged in the last part of the last century to cope with the uncertainty in fisheries systems, providing a framework to formalize its incorporation in the decision making process.

1.2.3 Management strategy evaluation

The management of fisheries systems is characterized by being subject to a great uncertainty. The uncertainty is derived from both, the natural variability in the system and the uncertainty in the different steps of the management process. MSE approach, also known as operational management procedure approach, arose as a tool to cope with large uncertainties and inconsistent information in the decision making process (Polacheck et al. 1999). It is widely used in fisheries management to evaluate the performance of management strategies, by means of simulation, before they are put in place. It consists in simulating the fish stocks and the fleets that exploit them together with the management process. One of the goals of MSE is to analyse the performance of different management strategies and identify those strategies that are robust to the uncertainties considered. The approach facilitates interaction between scientists and stakeholders in the management process (deReynier et al. 2010). Furthermore, it promotes the use of HCRs, which automate the generation of the management advice, and hence, removes the influence of politics in the decision making process (Punt and Donovan 2007).

The first application of MSE was developed by the international whaling commission (IWC) in the 1980s. In 1982, due to the uncertainty in the data available and the impossibility to obtain a reliable estimate of the abundance of whale populations, the IWC decided to impose a moratorium in the commercial fishing of whales from 1986 onwards (Kirkwood 1997). In order to be able to end with the moratorium the IWC scientists looked for a procedure that was robust to the inherent uncertainties and was able to ensure, with high probability, that the management objectives were fulfilled. The process of developing the management procedure took six years. Initially, they defined several management procedures and as experimental testing was not possible, they were tested by means of simulation. The management procedures finally selected performed quite well managing simulated whale stocks and it was adopted by the IWC. Paradoxically, the IWC was the pioneer in adopting a management procedure developed following an MSE but it has never been implemented because the moratorium is still in place (Punt and Donovan 2007) (https://iwc.int).

The simulations that run under MSE approach have two main components, the operating model (OM) and the management procedure (MP). The OM represents the system that is being managed (the 'true' population). It simulates the system using plausible hypothesis about its dynamic. As a minimum, it includes a single stock and a single fleet that exploits it. But it can also be represented by a more realistic system with many stocks and fleets or even by a full ecosystem model such as Atlantis (Fulton et al. 2005).

The explicit simulation of the management procedure is what distinguishes the MSE approach from other simulation approaches. It reproduces the management strategy that is being tested, from the data collection to the generation of the management advice. The link between the OM and the MP is done through the observation model. This model generates the sampling data which can include biological data, time series of stock abundance obtained through scientific surveys at sea, catch and effort data from the fleets or others. The data is then used to feed the assessment model which generates an estimate of the *true* fish population status. In the MSE literature this population is known as the *perceived* population. The management advice is then generated by a HCR based on the *perceived* population. The management advice is normally a TAC but could also correspond with technical measures like spatio-temporal closures or minimum landings sizes. Finally, the link between the management procedure and the operating model is done through the implementation model. This model describes how the management advice obtained in the MP is really implemented in the OM. The managers could modify the management advice based on other factors and/or fishers could not catch exactly the TAC.

The simulation of the whole MP, together with the simulation of the response of fishers to the management advice, make that the catch in the OM does not necessarily correspond with the TAC obtained in the MP. Punt et al. (2016) state that to be qualified as an MSE the simulation should include at least some kind of implementation error.

After the pioneer approach of the IWC, one of the most relevant MSE implementations, for the commercial importance of the resource and the scope of the process, was that of southern bluefin tuna (Polacheck et al. 1999). In a process that expanded from 2002 to 2011 a management procedure was agreed on July 2011 and the TAC has been set according to the HCR defined in this MP since that year. It is applied every three years and it provides TAC advice for the next three. It is planned to develop a new management procedure in 2021 to account for the new data available (https://www.ccsbt.org/en/content/management-procedure).

The first applications of MSE were focused in the performance of MPs at stock level and they used single stock approaches (Garcia et al. 2011, Kell et al. 2006b, Polacheck et al. 1999, Punt and Smith 1999). However, nowadays the multi-stock and multi-fleet approaches are becoming more frequent (Dichmont et al. 2008, Garcia et al. 2019b; 2017a, Prellezo et al. 2016). However, most of these applications do not include a complete uncertainty analysis. This problem was already pointed out by Kraak et al. (2010).

1.3 Validation of mathematical models

Simulation models are simplified descriptions of reality and can never replicate the real world exactly. Hence, validation of models is needed to ensure that the model describes the real system well enough for the intended purpose. The absolute validation of ecosystem models is impossible because the ecosystems are open systems Oreskes et al. (1994). Nevertheless, we can gain confidence in the model through the application of validation techniques.Validation and verification of mathematical models arose in the 1950s. Sargent and Balci (2017) conducted a historical review of the evolution in validation since the 1950 that is summarized here. The concepts of validation and verification of simulation models arose in the 1950s when the use of the computers was extended. However, at that time, validation and verification methodologies were not available and they were rarely conducted. Furthermore, there was confusion about the meaning of both terms. Fishman and Kiviat (1968) were the first authors defining validation formally. From 1970 to 1990 the need of conducting validation and verification of simulation models to demonstrate the reliability of models was acknowledged. In those years, there were few papers published and most of the work was included as book chapters. Since 1990, verification and validation of models is a requirement in many organizations and new developments and research papers increased enormously.

The controversy in the use and definition of validation has been a constant since the beginning (Schmolke et al. 2010). Oreskes et al. (1994) argue that verification and validation can never be accomplished because "natural systems are never closed and model results are always non-unique". However, other authors like Schmolke et al. (2010) and Rykiel (1996) advocate the use of validation for the process of ensuring that the model behaviour is good enough for the stated purpose. The validation and verification of simulation models is a process that goes hand in hand with the development process. It is almost impossible to ensure that a model is valid over its full application domain, instead the model is tested in different case studies and scenarios until enough confidence in its suitability is build (Sargent 1991).

Augusiak et al. (2014) made a review on the use of validation and verification terms in mathematical modelling. They found that validation term is frequently used with two different meanings:

- Assessment of the implications of errors made in the design and the implementation in the model output, and whether the output behaviour exhibits the required accuracy with regard to the model's intended purpose. The assessment is mainly built on comparing model output to data that were preferably not used for model development.
- The entire process of forming the decision whether and when a model is suitable to meet its intended purpose by building confidence in model applications and increasing the understanding of model strengths and limitations.

Verification has been also used with the two meanings above, but the most commonly used definition for verification is "Assuring that the computer programme and implementation of the conceptual model are correct." Sargent (1991) distinguishes between *conceptual model* and *computerized model*. The *conceptual model* refers to the graphical/mathematical representation of the model and *computerized model* to its implementation as a computer program. With this differentiation, validation is carried out on the *conceptual model* and verification on the *computerized* one. Although the *computerized model* is an invaluable tool to perform the validation of the *conceptual model*.

In what all the authors agree, is that validation and verification needs to take place in every stage of simulation model development and application. Furthermore, there is not a universal technique that can be used to validate models and they can not be validated absolutely. The validation of models is case and objective specific.

Balci (1997) presented a long list of techniques for the validation of simulation models divided in four groups:

- *Informal* techniques which rely on human reasoning and lack mathematical formalism (external audit, face validation, ...);
- *Static* techniques which are concerned with accuracy assessment on the basis of characteristics of the static model design and source code (cause-effect graphing, data analysis,...);
- *Dynamic* techniques which evaluate the model based on execution behaviour (graphical comparisons of the results, sensitivity analysis, ...);
- *Formal* techniques which are based on the mathematical proof and correctness (induction, inference...).

The dynamic techniques are the most numerous. One of the most widespread technique in this group is sensitivity analysis.

1.3.1 Global Sensitivity Analysis

The use of sensitivity analysis arose in the second part of the last century. In 1957, Maffey already forecasted the importance that sensitivity analysis would have in the future (Maffei 1957). The initial applications were applied in linear models and their use in highly non-linear models was only valid locally. The use of sensitivity analysis in nonlinear models was generalized from 1960, when the first screening methods appeared. These methods are able to rank the input factors of a model according to their impact on the results, but do not provide a quantification of the impact. The first methods consisted on moving one factor at a time and did not included interactions (Li 1962, Watson 1961). Some years later methods that consider interactions were developed (Cotter 1979). The most popular screening method, the Morris elementary effects method, was published by Morris in 1991 (Morris 1991).

Variance decomposition methods are more advanced than the screening ones and apart from providing a rank of the input factors, also provide an estimate of the contribution of each input factor to the output variance. The first variance decomposition method, the Fourier Amplitude Sensitivity Test (FAST), was introduced by Cukier in 1973 (Cukier et al. 1973). The FAST method consist on defining a curve to search the multidimensional sampling space and using the multidimensional Fourier transformation to decompose the variance using an ANOVA like approach. The FAST sensitivity index only provides the main contribution of the input factors, i.e, they do not included the contribution of the interactions between input factors. In 1993, Sobol introduced an alternative variance decomposition method based on the decomposition of the model as a sum of elements which depend on the different dimensions of the model (Sobol 1993). Furthermore, the elements can correspond with a single dimension or a group of them and they are a function of the integrals of the original model over the domain of the dimensions. In the framework of Sobol variance decomposition method, Homma and Saltelli (1996) introduced the concept of main effect to account for the effect of interactions and avoid the computation of all the terms in the decomposition of the model. Later, Saltelli et al. (1999) applied this concept to the FAST method and extended it to allow the calculation of the main effects. Nowadays, Sobol decomposition method is one of the most widespread method, surely because it is easy to understand, easy to implement and model-free. Two of the main drawbacks of this method are its high computational cost and its inability to represent the output's uncertainty correctly if the model output is highly skewed (Borgonovo et al. 2011, Pianosi and Wagener 2015).

Rabitz (1989) conducted a review of sensitivity analysis methods in the framework of molecular systems and concluded that modelling can not be considered complete without a sensitivity analysis. At that moment, GSA methods were emerging and the applications in real modelling implementations were scarce. Almost two decades later, Saltelli et al. (2006) analysed the use of sensitivity analysis in practice, despite the advances in the development of GSA methods, they found that most of the applications of sensitivity analysis were based on the one factor at a time approach, that is only correct when the model is linear. They also proposed a guide of good practices to apply GSA. Last year, they carried a similar review Saltelli et al. (2019) but with the focus on highly cited papers only. They found that there has been an advance in the use of GSA methods in modelling papers performing some sensitivity analysis. However, still 42% of the articles did not explore the domain of the model properly. Recently, Norton (2015), Pianosi et al. (2016) and Plischke (2016) conducted a review of GSA methods. Norton (2015) provide an informal introduction to the aims and methods of sensitivity analysis. Pianosi et al. (2016) carry out a systematic review of sensitivity analysis methods where apart of describing the methods available they provided a workflow for the application of sensitivity analysis. In turn, Plischke (2016) focused in recent advances in distributional sensitivity analysis and the use of metamodelling to conduct it. While traditional GSA methods uses output variance to characterize the uncertainty in the model output, distributional sensitivity analysis considers the entire distribution of the output. In multi-modal or highly skewed models where variance does not represent the uncertainty adequately distributional sensitivity analysis could be a good alternative to traditional methods.

GSA is a valuable approach in the validation process of simulation models (when validation is understand as the second definition in the previous section) and the verification process. The ranking of the input factors and the decomposition of the variance provide a deep understanding of the internal behaviour of the model. Furthermore, unexpected relation between input factors and output variables can reveal an incorrect definition in the conceptual model. Additionally, variance decomposition methods provide a precise estimation of the effect of input factors and their interactions in output variables which can highlight possible errors (in the implementation of the model, its structure or conditioning) if the obtained effects are contradictory.

1.4 Motivation of the PhD

1.4.1 Development of `FLBEIA`

At the beginning of this century the European Commission started using multiannual management plans for the management of fish stocks in European Waters (e.g. EC (2004a;b; 2006)). These multiannual plans should be evaluated to ensure that they met the pre-defined management objectives. In the first decade of the century the scientist started to use quantitative biological MSE models to evaluate these management plans (Kell et al. 2006a, Kelly and Codling 2006, Needle 2008). If necessary economic indicators were calculated *a posteriori* without any feedback between the fleets and the stocks. Furthermore, most of the approaches were single stock and single fleet. However, many fleets catch several stocks simultaneously (the so called mixed fisheries) and an adequate economic analysis should include all the stocks caught. Furthermore, the stocks are exploited by several fleets. Hence, to be able to carry out adequate bio-economic evaluations of multiannual management plans, the necessity of developing multi-stock and multi-fleet MSE simulation models was identified (STECF 2010).

AZTI is a Basque technological centre focused in marine research and food technology; and most of the fisheries research related to fisheries management in Basque Country is carried out by its researchers. Furthermore, they participate actively in the working groups and organizations that deal with the problems that affect Basque fishing fleets. Thus, a decade ago, we, as AZTI's researchers, already had experience in developing single stock and multi-fleet case specific MSE simulation models (Garcia and Prellezo 2009, Garcia et al. 2008; 2011, Murua et al. 2010). Although there were many components of the models that were common in all the cases, in each new application we had to start from scratch to develop a new model. Hence, we decided to develop a generic multi-stock and multi-fleet MSE model. The model should be generic enough to be applied to Basque fleets and the stocks that they exploit. Furthermore, it should be flexible enough to allow the incorporation of new developments easily. The model was named `FLBEIA` and is the cornerstone of this thesis.

1.4.2 Global Sensitivity Analysis

The motivation to conduct a GSA of an FLBEIA application was the need for enhancing the validation of the model and the need of having a deeper understanding of the model behaviour. Furthermore, the little use of GSA in MSE applications motivated the elaboration of a set of guidelines to promote and facilitate its use. The definition of selection and convergence criteria arose as a tool to ensure the robust application of the Morris elementary effects screening method (Morris 1991) when combining it with the Sobol variance decomposition method (Sobol 1993).

1.5 The Hypothesis and Objectives

The first part of this thesis has been dedicated to develop FLBEIA model and the second part to advance in its validation process. In both parts, the model has been applied to a complex case study with several stocks and several fleets. In relation with the application of FLBEIA like simulation models and GSA methods this thesis raises *three hypotheses*:

- The input factors that are usually considered uncertain are not always the most important;
- the existing convergence criteria in Morris method are too demanding when the objective is to select a certain fixed number of factors;
- the selection criteria used in Morris method lead to a suboptimal selection of factors.

The veracity of the hypotheses have been evaluated through two main objectives. The first one is related with the development of FLBEIA and states the properties that the model must have to respond to existing needs. In turn, the second objective relates to the validation process and seeks to facilitate the application of GSA in fisheries management simulation models.

The *first objective* is to develop a generic multi-stock and multi-fleet MSE simulation model that:

- is general enough to be applied to stocks and fleets with different structures and dynamics.
- can incorporate observation errors in the observation model;
- can easily incorporate new assessment models;

- can be used to evaluate different harvest control rules and technical management strategies.

The *second objective* is operationalized in three milestones:

- Application of `FLBEIA` to a complex case study and deepen in the validation of the model applying a GSA;
- proposition of a set of guidelines to facilitate the application of GSA in fisheries management simulation models;
- definition of an efficient procedure to carry out a quantitative GSA of complex simulation models.

1.6 The Structure

The thesis has been divided in seven chapters including the introduction which corresponds with the present one. The second chapter provides a detailed description of the `FLBEIA` model, including the mathematical formulation of the processes that build up the model and the structure of the algorithm. The third chapter, on the one hand includes a description of the Morris and Sobol GSA methods, and on the other hand, presents the new criteria and guidelines proposed in this thesis to promote the application of GSA methods. In the fourth and fifth chapters we focus on the application of the methods presented in the previous chapters, `FLBEIA` and GSA. In the fourth chapter we test the new landing obligation policy and new biological reference points in a complex case study. In turn, in the fifth chapter, we use the same case study to apply the criteria and guidelines proposed previously. In the sixth chapter we describe the software that has been developed in the framework of this thesis; the `FLBEIA` model distributed as a `R` package (R Core Team 2018), the `FLBEIAShiny` package use to analyse the results and the `R` functions developed to implement the criteria defined in Chapter 3. The last chapter of the thesis, exposes the conclusions obtained throughout the thesis that have been separated in four sections: the use and development of `FLBEIA`, the proposed selection and convergence criteria, GSA in fisheries simulation models and GSA in practice. We finalize the chapter with a proposal of several research lines to continue with the work initiated in this thesis. An scheme of the thesis with the chapters and their interactions is shown in Figure 1.3.

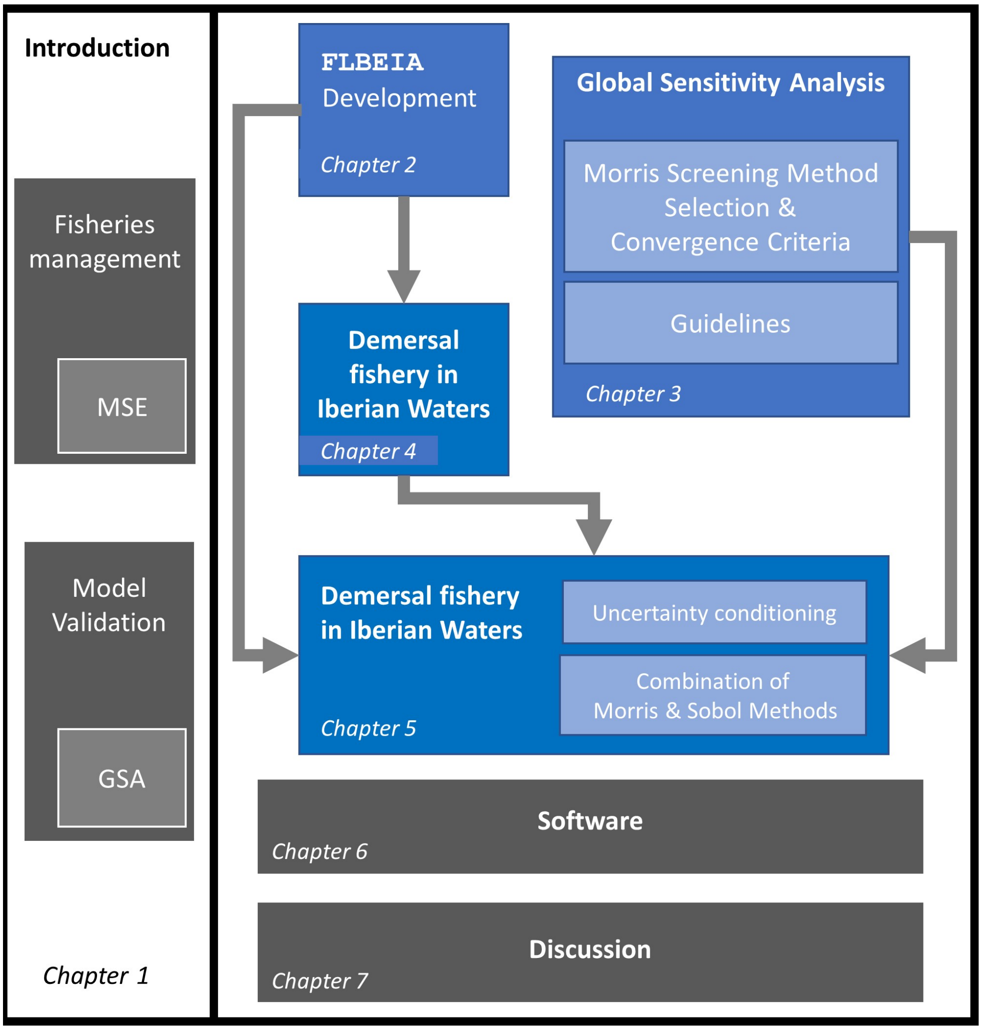

Figure 1.3: Structure of the manuscript.

Chapter 2

FLBEIA: A model to conduct bio-economic impact assessment of fisheries management strategies

A summary of this chapter, describing **FLBEIA** *model in general terms, has been published in* ***SoftwareX*** *scientific journal: "*FLBEIA*: A simulation model to conduct Bio-Economic evaluation of fisheries management strategies"*

2.1 Introduction

In the previous chapter we described the evolution throughout history of mathematical modelling in fisheries management. Management of fisheries systems is necessary to ensure a sustainable and efficient exploitation of marine resources (Gordon 1954). The scientific advice is produced routinely by regional fisheries management organizations to inform administrations about fisheries management measures. Traditionally, fisheries management has relied on biological models. However in recent years, the focus on mathematical description of economic and social dimensions has increased driven by the ecosystem based fisheries management approach (Curtin and Prellezo 2010, Pikitch et al. 2004). According to this approach, the management advice should be based not only on biological criteria but also on economic and social ones. Therefore, approaches that integrate these three disciplines are needed. However, such approaches are currently scarce and usually case specific. Furthermore, scientists tend to focus on biology or economy whereas sociology is still quite undeveloped (Plaganyi et al. 2013).

Multi-annual management plans (MMPs) provide a mechanism to automatically set harvest rates and fishing opportunities for a number of years using pre-agreed formulas (i.e. HCRs). The food and agriculture organization of the united nations, FAO, defines MMPs as a key toolbox in the precautionary approach to fisheries management and states that MMPs should not be put in place before proving that they will not lead to undesirable results (FAO 1996). On the same line, Beddington et al. (2007) highlight the importance of testing harvest strategies in the success of fisheries management. The European Commission (EC) introduced MMPs in the 2002 reform of the CFP as a tool to recover endangered stocks (Beddington et al. 2007). Before approving a new MMP, the EC runs an impact assessment, a process where the likely biological, economic and social responses to the MMP are evaluated (EC 2009, Simmonds et al. 2011). Biological impact assessment of MMPs are usually conducted under the MSE approach (Butterworth and Punt 1999, De la Mare 1998, Punt et al. 2016, Punt and Donovan 2007). The MSE implementations have been generally biologically oriented, single stock, single fleet and case specific (see for example Garcia et al. (2011), Kell et al. (2006a), Punt and Smith (1999)). There are many examples where the biological impact assessment was carried out using MSE but few of them included economy in the simulations (Dichmont et al. 2008, Garcia et al. 2017a; 2013, Pilling et al. 2008, Prellezo et al. 2016). Economic evaluation were usually run afterwards on top of biological models, but the models used were not coupled or integrated and not even congruent (Garcia et al. 2011, STECF 2010).

A review of bio-economic models which focus on assessing the performance of management strategies can be found in (Prellezo et al. 2012). Apart of the models revised in that paper, BIOMAS (BIO-economic Modelling and ASsessment, Ives and Scandol (2013)), Fishrent (Salz et al. 2011, Simons et al. 2014) and IAM (Impact Assessment Model, Guillen et al. (2013)) are recent developments of multi-stock and multi-fleet integrated bio-economic models. BIOMAS was primarily developed to be used as multi-stock assessment model and the economic and management process components are fairly rudimentary. Fishrent and IAM are annual and do not follow strictly the MSE approach. They allow testing management strategies by means of simulation but they do not simulate the whole management process. They do not include the observation nor the assessment processes, and hence they cannot assess the uncertainty associated to them. The main advantage of Fishrent and IAM is that in addition to simulating the fishery system they also allow to estimate the parameters of the management strategy that maximize the profitability of the fleets. Apart from these bio-economic simulation-optimization models there are other approaches to deal with potential trade-offs between biological, economic and social dimensions such as viability theory (Gourguet et al. 2013) or cost benefit analysis (Kronbak et al. 2009).

There exist several examples of integrated bio-economic models developed under the MSE approach (see for example Andersen et al. (2010), Bastardie et al. (2009), Dichmont et al. (2008)). However, they are all case specific models built to address case specific problems. Integrated bio-economic models that follow the MSE approach, that satisfy the requirements of impact assessment and that can be applied in a wide range of case studies and management strategies are therefore needed (STECF 2010).

To respond to this need we developed `FLBEIA` (Bio-Economic Impact Assessment using `FLR` (Fisheries Library in R)), a bio-economic simulation model, aimed at facilitating the development of impact assessment under the MSE approach. The model allows the bio-economic evaluation of a wide range of management strategies in a great variety of case studies and scenarios. To facilitate this, the model has been developed in a composable [1] manner (Jordan et al. 2011). The model has a covariates module that allows new variables of interest to be introduced, such as, for example, social or environmental indicators. `FLBEIA` is available as an `R` statistical software package (R Core Team 2019), it depends on basic `FLR` libraries (Kell et al. 2007) and the code is freely available at http://github.com/flr/FLBEIA.

The rest of the chapter is structured as follows, first `FLBEIA` model is described in general terms, the philosophy behind it and its main features. Then, the processes that build up the fishery system are described, what do they represent, how `FLBEIA` interlinks them and the specific functions available to model them. In the third section the validation and verification of `FLBEIA` thorough its development process is described. Finally, the usefulness of the model to conduct impact assessment of management strategies is discussed identifying its strengths and weakness in relation to other existing tools and models.

2.2 Model description

`FLBEIA` is a `R` (R Core Team 2018) library which makes use of `FLR` tools (Kell et al. 2007). `FLR` provides the basic pieces to construct the model and `FLBEIA` assembles them to build a composable bio-economic model. The basic `FLR` packages, `FLCore`

[1] *Composability*: a model is nothing more than the 'sum' of its parts, which can be individually modelled and then put together, as defined in Jordan et al. (2011).

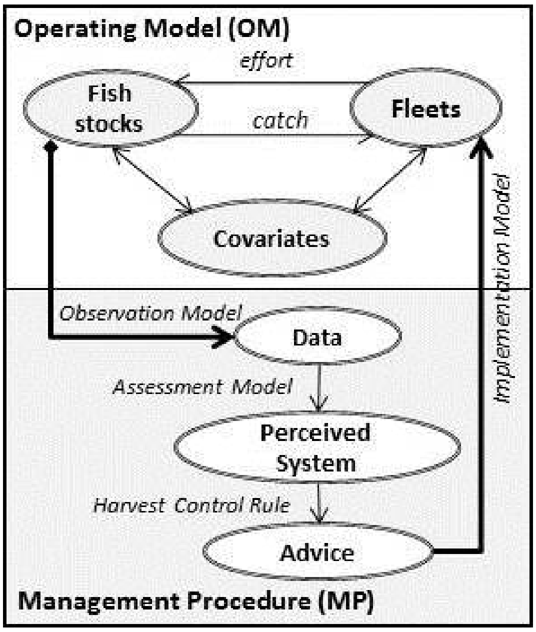

Figure 2.1: Conceptual diagram of `FLBEIA` which shows the main components of the model and how they are interlinked. Figure modified from Garcia et al. (2013).

and `FLFleet`, provide the data containers (the classes) of the input and output objects and the methods to operate with them. `FLash` and `FLAssess` packages are used in the advice module to do some of the calculations in the HCRs. Finally, `FLSa4a`, `FLXSA`, `FLSAM` or other stock assessment model packages, can be used within the assessment module to generate stock status estimates. All these R packages are freely available in `http://github.com/flr`.

`FLBEIA`'s simulation algorithm (from here referred as *the algorithm)* is divided into two blocks, the OM and the MP (Figure 2.1). In the MSE approach two worlds must be distinguished, the *real* world, which represents the fish stocks and the fleets simulated in the OM, and the *perceived* world, which corresponds to the observations or the estimations of the *real* world in the MP. In `FLBEIA` the OM is made up of fish stocks, fleets, covariates and their interactions. In turn, the MP is formed by the data, the *perceived* system and the advice, generated by the observation model, the assessment model and the HCR, respectively.

Thus, when a management strategy is tested, the management advice is not based on the *real* system simulated in the OM but on the *perceived* system obtained through the observation and/or assessment models in the MP. In this way, when a management strategy is evaluated, not only is the strategy itself evaluated, but also its performance in conjunction with the data collection and the assessment model.

The uncertainties in the fishery systems were described and categorized by Francis (1997) into six groups. Three of them relate to the dynamics of the fishery system (process, implementation and institutional uncertainty), and the other three refer to the accuracy of the management process (observation, model and estimation uncertainty). The impact of all these uncertainties, except institutional uncertainty (which relates to the misspecification of management objectives), can be evaluated using `FLBEIA`.

The algorithm has been developed by composition (Jordan et al. 2011), which main components are shown in Figure 2.1. The fishery system has been broken up into several modules (dark grey rectangles in Figure 2.2) and several functions have been implemented to model each of them. The modules correspond with the most basic processes of the fishery system that are explicitly modelled within `FLBEIA`. The modules are grouped into bigger components (light grey rectangles in Figure 2.2) which are connected by the main function `FLBEIA`. Implementing the algorithm modularly eases checking and debugging, and allows for increased complexity adding extra modules (Jordan et al. 2011). If in a specific case the functions available do not satisfy the needs for a specific module, new functions can be implemented and used within `FLBEIA`.

The assembly within `FLBEIA` follows a top-down approach (Figure 2.2). The algorithm is divided into three main levels. The functions in the two highest levels are fixed and those in the third level are selected by the user:

First Level. The main function (`FLBEIA`, see Figure 2.2), is in the first (top) level, and it calls second level functions sequentially.

Second Level. The functions in this level are called by the main function in the order shown in Figure 2.2 . The functions in the OM (`biols.om`, `fleets.om` and `covar.om`) control how the fish stocks, the fleets and the covariates are projected each season in the future. Those in the MP (`observation.mp`, `assessment.mp` and `advice.mp`) control how the observed data, the *perceived* system and the stock based advice are generated each year.

Third Level. The functions in this level need to be chosen by the user (dark grey rectangles in Figure 2.2) and are called by the second level functions. The user can choose among existing functions or develop new ones. Besides, depending on how the third level functions are coded, in turn, they can call functions at lower levels (fourth and so on). Several functions have been implemented to

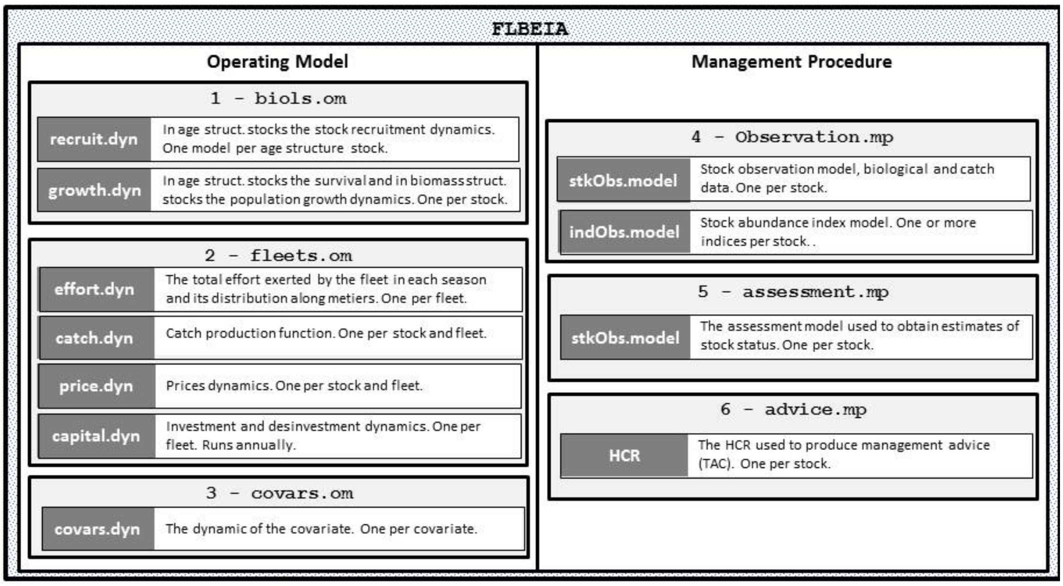

Figure 2.2: Scheme showing the assembly of the functions within `FLBEIA` algorithm. The main function `FLBEIA` calls the functions in the light grey rectangles in the order indicated. In turn these functions call the functions in the dark grey rectangles. The dark grey rectangles correspond with the most basic processes of the fishery system modelled within `FLBEIA` and the functions that model them must be declared by the user. Figure taken from Garcia et al. (2017b).

model each process and new ones can be coded in `R` and used within `FLBEIA`.

In the first step of the simulation, the biological populations (fish stocks) are projected one season ahead, independently, stock by stock. Afterwards, fleets are projected independently one by one and four processes are modelled: effort allocation, catch production, price formation and capital dynamics.

The OM projects the covariates independently into the future using each own dynamic model. Covariates are used to allow including in the simulation of the *real* system variables that are not included in the biological and fleet OMs. The model that describes their dynamic must be coded in `R` following the input and output structure used in `FLBEIA`.

The management procedure takes place once a year for each stock. In seasonal models the season when it takes place is selected by the user and depends on the stock. The observed data is divided into two types: stock data and abundance indices [2]. Stock data comprises catch data (landings and discards at age or biomass

[2] Abundance indices are time series that are correlated with the abundance of the stock.

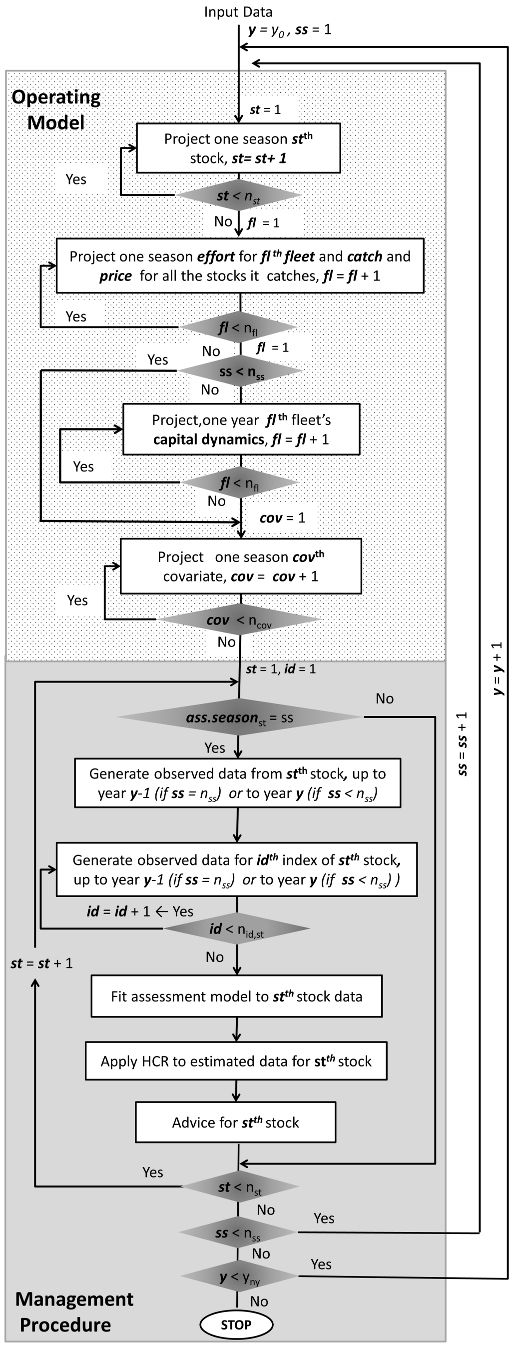

Figure 2.3: Flow chart of `FLBEIA`'s algorithm explaining how it moves along the simulation. White rectangles represent the modules and grey diamonds contain the condition to move from one module to the next. y, ss, st, fl, cov and id are the counters for year, season, stock, fleet, covariate and abundance index respectively,y_0 and y_{n_y} corresponds to the first and last simulation years, $ass.season_{st}$ to the assessment season for st-th stock, and n_y, n_{st}, n_{fl}, n_{cv}, n_{ss} and $n_{id,st}$ to the number of simulation years, stocks, fleets, covariates, seasons and abundance indices for st-th stock respectively. Figure modified from Garcia et al. (2017b).

level) and biological data (maturity, weight and natural mortality) at stock level. Abundance indices are simulated by stock and each stock can have more than one index. Regarding fleets the only data that is observed in the management procedure are the landings and discards and they are simulated in an aggregated way at stock level. The simulated data, stock data and abundance indices, are used to feed the stock specific assessment models. The estimates obtained through the assessment models, usually estimates of stock biomass and exploitation level, provide estimates of the *real* stocks simulated in the OM. In the MSE literature these estimates are known as the *perceived* stocks. Then, HCRs are applied to each *perceived* stock to obtain the management advice. Hence, the management advice is not based on the status of the *real* stock but on its estimate, the *perceived* stock. Finally, this information is transmitted to the fleets in the OM and the loop starts again.

The symbols used along the text, figures, tables and equations are listed in Appendix A.

2.2.1 The Operating Model

The OM is the part of the model that simulates the true dynamics of the fishery system (the *real* population). Biological populations and fleets are its essential elements and they interact through fishing effort and catch. Covariates are part of the OM but they are not mandatory. If necessary, they could interact with the stocks and the fleets.

2.2.1.1 Biological Operating Model

The biological OM is formed by the stocks that can be age structured or in biomass. Three models are available to describe stock dynamics.

In the first model all the stock's data, in both the historical and projection periods, is given as input data. It implicitly assumes that population growth is independent from the catch produced by the fleets. This model can be useful, for example, in the case where nothing is known about the stock dynamics, but its incorporation into the model is justified by the economic importance of the stock to a particular fleet.

A second model projects age structured populations one season ahead using a stock-recruitment model [3] for incoming recruitment and an exponential survival

[3] *Stock-recruitment* models relate stock's reproductive potential with the entry of new individuals into the population or fishery. Different indicators can be used as a proxy for stock's reproductive

equation (Quinn and Deriso 1999) for existing age classes. Fish individuals are aggregated in cohorts that comprise individuals born in the same year and season. All the individuals move from one age class to the next on 1st of January regardless of the season in which they were born. The catch is assumed to take place instantaneously in the middle of the season. Mathematically, for the first season, $ss = 1$, the model can be written as:

$$PN^{u,1}_{a,y} = \begin{cases} \phi_{\text{rec}}\left(RP_{y=y-a_0, ss=ss_{spwn_1}}\right) & a = a_0 \\ (PN^{u,n_{ss}}_{a-1,y-1} \cdot \mathrm{e}^{-\frac{M^{u,n_{ss}}_{a-1,y-1}}{2}} - CN^{u,n_{ss}}_{a-1,y-1}) \cdot \mathrm{e}^{-\frac{M^{u,n_{ss}}_{a-1,y-1}}{2}} & a_0 < a < a_+ \\ (PN^{u,n_{ss}}_{a_+-1,y-1} \cdot \mathrm{e}^{-\frac{M^{u,n_{ss}}_{a_+-1,y-1}}{2}} - CN^{u,n_{ss}}_{a_+-1,y-1}) \cdot \mathrm{e}^{-\frac{M^{u,n_{ss}}_{a_+-1,y-1}}{2}} + & \\ (PN^{u,n_{ss}}_{a_+,y-1} \cdot \mathrm{e}^{-\frac{M^{u,n_{ss}}_{a_+,y-1}}{2}} - CN^{u,n_{ss}}_{a_+,y-1}) \cdot \mathrm{e}^{-\frac{M^{u,n_{ss}}_{a_+,y-1}}{2}} & a = a_+ \end{cases}$$

where PN denotes the number of individuals, M the natural mortality, CN the catch in number of individuals and a, y, u and ss are the subscripts for age, year, seasonal cohort and season, respectively. a_+ is the plus group [4], n_{ss} is the number of seasons, a_0 is the age at recruitment, ss_{spwn_j} is the season when recruitment of j-th seasonal cohort is spawn and ϕ_{rec} denotes the stock-recruitment model. ϕ_{rec} can correspond with any of the stock-recruitment models available in the `FLCore` library of `FLR` (Kell et al. 2007) or a new one can be defined in `R` and used within the simulation.

RP is the reproductive potential of the stock, the variable used as recruitment predictor. For a given year and season RP is calculated as:

$$RP_{y,ss} = \sum_{a=a_0}^{a_+} \sum_{u=1}^{n_u} PN^{u,ss}_{a,y} \cdot w^{u,ss}_{a,y} \cdot fec^{u,ss}_{a,y} \cdot mat^{u,ss}_{a,y} \cdot \mathrm{e}^{-(M^{u,ss}_{a,y} \cdot M^{u,ss}_{spwn\,a,y} + F^{u,ss}_{a,y} \cdot F^{u,ss}_{spwn\,a,y})}$$

where n_u is the number of seasonal cohorts of the stock, fec is the fecundity of the individuals, mat the proportion of matured individuals, and M_{spwn} and F_{spwn} are the proportion of fishing and natural mortality that occurs before spawning in season ss, respectively.

For subsequent seasons,

potential: total stock biomass, spawning stock biomass or egg production among others.

[4] The *plus group* is an artificial age group where individuals of age a_+ and older are merged.

$$PN_{a,y}^{u,ss} = \begin{cases} \phi_{\text{rec}}\left(RP_{y=y-a_0,ss=ss_{spwn_{ss}}}\right) & a = a_0 \\ (PN_{a,y}^{u,ss-1} \cdot e^{-\frac{M_{a,y}^{u,ss-1}}{2}} - CN_{a,y}^{u,ss-1}) \cdot \mathrm{e}^{-\frac{M_{a,y}^{u,ss-1}}{2}} & a_0 < a < a_+ \end{cases}$$

.

Populations aggregated in biomass are projected using the Pella-Tomlinson growth model (Pella and Tomlinson 1969). Mathematically:

$$PB_{ss,y} = \begin{cases} PB_{y,ss-1} + \phi_{\text{pop}}(PB_{y,ss-1}) - CB_{y,ss-1} & ss \neq 1, \\ PB_{y-1,n_{ss}} + \phi_{\text{pop}}(PB_{y-1,n_{ss}}) - CB_{y-1,n_{ss}} & ss = 1, \end{cases}$$

where PB denotes total population biomass, CB catch in biomass, and ϕ_{pop} represents the seasonal population growth model. The following parameterisation of the Pella-Tomlinson growth model is implemented in `FLBEIA`:

$$\phi_{\text{pop}}(PB_{y,ss}) = PB_{y,ss} \cdot \frac{\iota_1}{\iota_2} \cdot \left[1 - \left(\frac{PB_{y,ss}}{PB_0}\right)^{\iota_2}\right]$$

where ι_1 represents the intrinsic growth rate, PB_0 the carrying capacity [5] of the population and ι_2 is a parameter used to give flexibility to the model ($\iota_2 = 1$ corresponds to traditional logistic growth model).

In the three population dynamics models, the catch is assumed to take place in the middle of the season in accordance with the fleet dynamics models defined in the fleets OM (see section 2.2.1.2).

In the equations in this section only CB, CN, F, PN, PB and RP are internally calculated by the model, the rest are input factors. All these equations are applied at stock level but the stock subscript has been omitted for simplicity.

2.2.1.2 Fleets Operating Model

Fleets OM is divided into four processes: effort, catch, price and capital. Effort allocation determines how much effort is exerted and how it is allocated among fleet's metiers [6]. Catch production gives the catch generated by each effort unit. Price formation calculates the price of the stocks. And finally, capital dynamics forecasts, only in the last season of each year, the variation in the number of fleet's vessels. Fleet's activity is divided into metiers and the projection into the future

[5] *Carrying capacity* is the maximum population size that the stock can support.

[6] *Metiers* are defined as fishing trips of a fleet that share the same characteristics in terms of gear used, fishing area and catch profiles (Marchal 2008).

is performed independently fleet by fleet. Thus, the models used to describe fleets' dynamics can differ from fleet to fleet.

Effort model. This model describes the fleet short-term dynamics (tactical behaviour). For each season it models how much effort is exerted and how it is distributed along metiers. In single-stock and single-metier fleets, assuming that it executes the effort that produces exactly the fleet's quota share, the proportion of the TAC that corresponds to the fleet, is a reasonable working assumption, but in multi-stock and multi-metier fleets the problem is not straightforward. For these fleets, two different groups can be distinguished: fleets that catch a number of stocks at the same time and are unable to discriminate among them, the so called *mixed fisheries*, and fleets that target only one stock at a time and whose metiers are seasonal, the so called *sequential-fisheries.* The models developed in `FLBEIA` capture the dynamics of these two types of fisheries.

In the first model, effort and its distribution along metiers are given as input data. Thus, the effort exerted by the fleet is independent of the state of the stocks and the management advice. Apart from this simple model, three effort dynamics models are available, two of which describe mixed fisheries dynamics and a third one that describes sequential-fisheries.

The first model used to mimic mixed fisheries is based on the Fcube method (Ulrich et al. 2011) and is used in `FLBEIA` to approximate mixed fisheries dynamics. The effort share along metiers is given as input data and only the total effort is estimated in each step. First, the effort corresponding to the quota-share of each of the stocks caught by the fleet is calculated, which returns a vector with one effort per stock. The final effort is selected based on this vector of efforts. The selection is done using different options (*min* the minimum, *max* the maximum, *mean* the mean, *previous* the most similar to the previous year effort and *stock-name* the effort that produces a catch level equal to the quota share of the aforementioned stock).

The second model used to simulate mixed fisheries dynamics calculates the total effort and the effort allocation among metiers that maximises profit. Profits are a function of the total effort exerted by fleet fl, E^{fl}, and how this effort is distributed along its metiers, $\gamma_{fl,1}, \ldots, \gamma_{fl,n_{mt,fl}}$, where $\gamma_{fl,i}$ is the proportion of effort exerted by fleet fl in metier i, and $n_{mt,fl}$ is the number of metiers in fleet fl. Moreover, profits can be decomposed as the difference between the gross value of the landings and the total variable and fixed costs. Mathematically:

$$\max_{\substack{E^{fl};\\ \gamma^{fl,1},\ldots,\gamma^{fl,n_{mt,fl}}}} \quad \text{profits}\left(E^{fl}, \gamma^{fl,1}, \ldots, \gamma^{fl,n_{mt,fl}}\right) =$$
$$\max_{\substack{E^{fl};\\ \gamma^{fl,1},\ldots,\gamma^{fl,n_{mt,fl}}}} \quad \sum_{mt}\sum_{st}\sum_{a} LB_{st,a}^{fl,mt} \cdot PR_{st,a}^{fl,mt} - E^{fl} \cdot \gamma^{fl,mt} \cdot VaC^{fl,mt} - FxC^{fl} \cdot n_V^{fl} \tag{2.1}$$

additionally, the maximization has several constraints:

$$\begin{cases} \text{and } \sum_{mt} \gamma^{fl,mt} = 1, \\ \gamma_{\min}^{fl,mt} \leq \gamma^{fl,mt} \leq \gamma_{\max}^{fl,mt} \\ E^{fl} \leq \kappa^{fl}, \\ CB_{st}^{fl} = \sum_a LB_{st,a}^{fl,mt} \leq QS_{st}^{fl} \quad \text{for } st \in \Xi^{fl}. \end{cases}$$

where mt is the subscript for metiers, LB is the landings in weight, where PR is the price of the fish landed, VaC the variable cost of fishing effort, which depends on the metier and is given as cost per unit of effort, FxC the fixed costs of each fishing unit, which is given at fleet level and in terms of cost per vessel, n_V is the number of vessels in the fleet, κ, the capacity of the fleet, is defined as the maximum effort that the fleet can execute in each season and Ξ is the set of stocks for which the constraint on catch must be fulfilled. In biomass dynamics populations, landings and prices are given at stock level. The first constraint guarantees that the effort-shares along metiers, the γ-s, sum up 1 and the second one limits the time the fleet can expend in each of the metiers, with an upper and lower bound, $\gamma_{\min}$ and $\gamma_{\max}$, respectively. The third one ensures that total effort is lower than the actual capacity of the fleet, κ. Finally, the fourth constraint describes the fulfilment of the management advice for a set of the stocks included in, Ξ. Ξ can be an empty set, in which case the fleet will not be constrained to comply with any quota share, QS, or it can be a subset of the stocks for which the fleet will comply with their quota share.

In the model used to describe sequential fisheries dynamics, historical effort dynamics guides the present performance of the fleet. Seasonally, each metier has only one target stock, and thus the metier is uniquely defined by the stock it catches. The expected effort to be allocated to each metier follows the historical trend, but it is restricted by the quota share of the fleet. In the case where the quota share is exhausted for a particular stock, then the remaining effort is reallocated among the rest of the metiers which target other stocks.

In the equations in this section year, season and unit subscripts have been omitted for simplicity.

Catch model. This model describes the relationship between catch and effort. Cobb-Douglas production model (Cobb and Douglas 1928) is widely used to describe production in industry in general and it is commonly used in economic fisheries models. Two variants of the model have been implemented, one at biomass level and another one at age level. The catch, in weight, derived from the Cobb-Douglas production model at biomass level is given by:

$$CB_{st}^{fl,mt} = \sum_{a=a_{0,st}}^{a_{+,st}} CB_{st,a}^{fl,mt} = \sum_{a=a_{0,st}}^{a_{+,st}} q_{st,a}^{fl,mt} \cdot (E_{fl} \cdot \gamma^{fl,mt})^{\alpha_{1,st,a}^{fl,mt}} \cdot w_{st,a} \cdot PN_{st,a}^{\alpha_{2,st,a}^{fl,mt}} \quad (2.2)$$

where fl and mt are the fleet and metier subscripts, respectively, q is the catchability [7], E is the effort exerted by the fleet, $\gamma^{fl,mt}$ is the proportion of effort of fleet's fl exerted in metier mt ($0 \leq \gamma^{fl,mt} \leq 1$ and $\sum_{mt} \gamma^{fl,mt} = 1$), and α_1 and α_2 are the output elasticities for effort and biomass, respectively. The catch is divided in landings and discards using the proportion of individuals retained onboard, ret, by fleet, metier, stock and age:

$$\begin{aligned} C_{st}^{fl,mt} &= L_{st}^{fl,mt} + D_{st}^{fl,mt} = \sum_{a=a_{0,st}}^{a_{+,st}} L_{st,a}^{fl,mt} + D_{st,a}^{fl,mt} = \\ &= \sum_{a=a_{0,st}}^{a_{+,st}} ret_{st,a}^{fl,mt} \cdot C_{st,a}^{fl,mt} + (1 - ret_{st,a}^{fl,mt}) \cdot C_{st,a}^{fl,mt} \end{aligned} \quad (2.3)$$

where L denotes landings and D discards and it can be given in number of individuals or total biomass. In populations aggregated in biomass catch and biomass are given at stock level, and the age subscript and the sum disappear. .

One of `FLBEIA`'s objective is to integrate the models used by biologists and economists in fishery science. Exponential survival model and the Cobb-Douglas production model are among the most popular models in fisheries biology and economy, respectively. Nevertheless, they cannot be coupled in a natural way. The exponential survival model describes population growth and catch in a continuous way

[7] *Catchability* is a measure of the fishing mortality generated on a stock by one unit of effort. It has different meaning depending on the mathematical model used to relate catch, effort and stock abundance.

and on the contrary, the Cobb-Douglas model describes catch production discretely and instantaneously. To overcome this discrepancy in the models implemented, it has been assumed that the catch takes place in the middle of the season.

Besides, for a sufficiently large effort, the catch derived from equation (2.2) can be higher than the biomass of the population. This problem has been solved truncating the Cobb-Douglass production function. The maximum catch level that any effort level can produce is defined as $\vartheta_{st} \cdot PB_{st}$, where PB_{st} is the biomass of the stock, ϑ_{st} is the maximum proportion of the total biomass that can be caught by the fishery and $0 < \vartheta_{st} \leq 1$ is set by the user. If E_0 is the effort that produces $\vartheta_{st} \cdot PB_{st}$ catch level, the catch for any effort level above E_0 is equal to $C(E) = \vartheta_{st} \cdot PB_{st}$. The proportion of catchable biomass, ϑ, is defined at stock level because it is a characteristic of the stock itself. Sometimes, even with this restriction, it could happen that when the catch of all the fleets is summed up, the total catch for certain ages is higher than the biomass. In this case, the catch of the affected age, CN_a, is equated to the corresponding abundance, PN_a, reducing the catch in the same proportion in all the fleets. This means that implicitly the catchability of the affected age class is reduced.

Price formation. Price changes at fleet and stock level and there are two models available to model its dynamic. In the first one price is given as input data and it is not changed in the simulation. In the second one we implement the model described in Kraak et al. (2004) where price depends on the ratio between current landings and landings in a baseline time period . As price usually depends on the landings of all the fleets, current landings may refer to the landings of the fleet itself or the total stock landings. Furthermore, price can vary independently by age. Mathematically the model is expressed as:

$$PR^{ss,fl}_{st,a,y} = PR^{ss,fl}_{0,st,a} \cdot \left(\frac{L^{ss,fl}_{0,st,a}}{\Gamma^{ss,fl}_{st,a,y}} \right)^{\beta^{ss,fl}_{st,a}}$$

where Γ corresponds to the landing of fleet fl, $LB^{ss,fl}_{st,a,y}$, or total stock landings in biomass, $\sum_{fl=1}^{n_{fl}} LB^{ss,fl}_{st,a,y}$, depending on the user choice. PR_0 is the base price corresponding to base landings, LB_0, and β is the price elasticity parameter.

Capital model This model describes the long-term dynamics of the fleets (strategic behaviour); the investment or disinvestment in new vessels or technological improvements. In `FLBEIA` the capital dynamics could be modelled through changes in fleet's capacity or changes in fleet's catchability (i.e. technological improvements). The capital can be given as input data and maintain it fixed for the whole simulation or it can vary according to the model described in Salz et al. (2011). This model relates the investment and disinvestment in new vessels with the ratio between the gross value (GV):

$$GV_y = \sum_{st}\sum_{a}\sum_{ss} L^{ss}_{st,a,y} \cdot PR^{ss}_{st,a,y}$$

and break even revenue (BER), that is the amount of revenue needed to cover both fixed and variable costs:

$$BER_y = \frac{CrC_y + FxC_y \cdot n_{V_y} + CaC_y}{1 - \frac{FuC_y + \sum_{mt}\gamma_y^{mt} \cdot VaC_y^{mt}}{Rev_y}}$$

where CrC is crew cost, CaC capital cost and FuC fuel cost. In turn, crew cost is formed by a fixed part and a variable part proportional to the gross value, mathematically:

$$CrC_y = FxS_y + \eta_0 \cdot GV_y$$

where FxS represents the fixed part of the whole crew wages and η_0 is the proportion of income dedicated to wages.

The maximum annual investment, $Inv_{\max}$, for each fleet is determined by:

$$Inv_{\max_y} = 1 - \frac{BER_y}{GV_y}$$

But only a certain proportion of this rate, η_1, is dedicated to increase the fleet, i.e.:

$$Inv_y = \eta_1 \cdot Inv_{\max_y}$$

Furthermore, investment in new vessels will only occur if the operational days of existing vessels is equal to maximum days. Finally, the investment/disinvestment decision, i.e. the variation in capacity, Υ, follows the rule below:

$$\Upsilon_{y+1} = \begin{cases} Inv_y \cdot \kappa_y & \text{if } Inv_y < 0 \text{ and } -Inv_y < \eta_2, \\ -\eta_2 \cdot \kappa_y & \text{if } Inv_y < 0 \text{ and } -Inv_y > \eta_2, \\ 0 & \text{if } Inv_y > 0 \text{ and } E_y < \kappa_y, \\ Inv_y \cdot \kappa_y & \text{if } Inv_y > 0 \text{ and } Inv_y < \eta_3 \text{ and } E_y = \kappa_y, \\ \eta_3 \cdot \kappa_y & \text{if } Inv_y > 0 \text{ and } Inv_y > \eta_3 \text{ and } E_y = \kappa_y. \end{cases}$$

where η_2 and η_3 stands for the limit on the decrease and increase of the fleet relative to the previous year, respectively. The increase in number of vessels is then obtained dividing the final investment in new vessels, Υ, by the maximum effort that a vessel can operate in a year, $E_{\max}$. Thus the new number of vessels is given by:

$$n_{V_{y+1}} = n_{V_y} + \frac{\Upsilon_{y+1}}{E_{\max}}$$

The formulas in this section are applied every year at fleet level but fleet subscript has been omitted for simplicity.

At present, models that dynamically change catchability are not available in `FLBEIA`. Catchability can vary over time but only if time dependent catchability is provided in the input data.

2.2.1.3 Covariates Operating Model

As indicated previously, the role of the covariates OM is to have room to incorporate into the model variables that are not included in biological and fleet OMs but are relevant to the fishery system or even to the ecosystem they belong to. The idea is similar to that of *effects* in BIOMASS model (Ives and Scandol 2013). The variables can be of any kind (biological, economic, environmental, social, ...) and appropriate models should be defined to simulate their dynamics and their interactions with other model components. At present the only function available maintains the covariates unaltered in the whole projection and it is used, for example, to store the variables of the capital dynamics function that have no place in biological and fleet components, namely: fuel cost, capital cost and salaries.

2.2.2 The Management Procedure

MP describes the management process and it runs annually. In `FLBEIA`, MP is divided into three modules, the observation model (the link between the OM and the MP), the assessment procedure and the management advice. The observation model together with the assessment procedure generate the *perceived* population based on which the management advice is calculated. The fish stocks and the fleets are observed to generate the necessary data to feed an assessment model. The *perceived* population in the assessment module is represented by the stock estimates or by a set of abundance indices per stock.

2.2.2.1 The Observation Model

The observation model simulates for each stock, independently, on the one hand, catch and biological data, and on the other hand, stock abundance indices. As most of the assessment models use annual data and at present all the assessment models available in `FLR` are annual, all the data is generated annually despite OM's seasonal dimension. Furthermore, all the observable variables can be subject to observation error.

In `FLBEIA` observed data contains data related to fleets' production (landing and discard data), to stock biology (natural mortality, fecundity and individual weight), to abundance indices, and to stock status (here defined as number of individuals and harvest rate). In reality, stock status data is not obtained through data collection, but applying assessment models to the observed data. However, in simulation studies knowing *real* stock status would be useful in cases where the interest is not on testing the goodness of the observation or assessment models but on assessing the performance of the management strategy in isolation. In `FLBEIA` there are two ways to obtain stock status indicators within the MP, through the assessment model, as it is done in reality, or through the observation model obtaining these indicators directly from the OM.

There are several models in `FLBEIA` to generate observed data. One of the models gathers data from fish stocks and fleets without error, including stock status data. The only difference with the OM data is that seasonal data is aggregated by year in the observation. A more realistic model generates data related to stock biology and fleets' production in age structured stocks adding two types of errors, an error associated with age determination and a multiplicative error associated to any other reason. The aging error is simulated using a square matrix, Γ, with dimension equal to the number of age classes. The element λ_{ij} in the matrix corresponds to the proportion of individuals of age i that are erroneously assigned to age j. This matrix is multiplied matricially with the vector of real data at age to obtain the observed data. The general error is then multiplied using a vector of positive values, ε_j, with length equal to the number of age classes of the stock. This vector is multiplied with the vector obtained after applying the aging error. Therefore, the observed value for age j is obtained using the following equation:

$$\chi_{MP_j} = \left(\sum_{i=a_0}^{A} \chi_{OM_i} \cdot \lambda_{ij} \right) \cdot \varepsilon_j \tag{2.4}$$

where χ_{OM} represents the value of the variable in the OM, and χ_{MP} the observed data in the MP. χ can be any observable variable (e.g., natural mortality-, landings-, maturity-at-age...).

Age structured stocks can also be observed at biomass level. First, the age dimension is collapsed by applying the correct procedure for each data type (sum for catch in numbers, weighted mean for individual weight, ...) and then a multiplicative error is applied as in (2.4).

Observed data for stocks in biomass can only be observed at biomass level. The observation errors are only multiplicative and they are introduced in the same way as for age structured stocks.

Abundance indices are an important source of information in fisheries management. They are time series related to the abundance of the stock. The most commonly used relationship is the linear model, i.e:

$$id_y = q_y \cdot P_y \tag{2.5}$$

where id denotes the abundance index, q the catchability of the index and P the abundance, in numbers at age or total biomass. The catchability can vary over time, therefore the violation of constant catchability assumption made in most of the stock assessment models could be tested using `FLBEIA`. In `FLBEIA`, abundance indices can be generated at age or biomass level. At age level the abundance is measured in number of individuals and at biomass level in total weight. In both cases equation (2.5) is used and q depends on the index and the age class. Multiplicative and aging errors can be introduced in the observed indices in the same way as for stock data in equation (2.4).

All the variables in the equations in this section are stock specific but the subscript has been omitted for simplicity.

2.2.2.2 The Assessment Procedure

The assessment models are applied independently stock by stock. They provide estimates of the status of the stocks simulated in the OM. Any assessment model coded in `R` can be used within `FLBEIA` if the input and output data have the right shape. `FLBEIA` does not provide any alternative assessment model but the assessment models available in `FLR` can be almost directly integrated in `FLBEIA`. Some of them have been already used, `FLXSA` in Garcia et al. (2013), and `FLa4a` (Jardim et al. 2014b) and `SPiCT` (Pedersen and Berg 2017) in Garriga et al. (2018) for example. Moreover, more complicated models have been used in an ad-hoc way, for example SS3 (Methot Jr and Wetzel 2013) in the evaluation of a management procedure for Iberian Sardine (ICES 2019) and an bayesian assessment model built in JAGS (Plummer 2003) to analyse management strategies for cod (González-Troncoso et al. 2015).

2.2.2.3 Management Advice

The management advice for each stock is generated by means of an stock specific HCR. All the implemented HCRs provide advice in terms of catch, i.e. they generate the TAC. To provide effort based management advice, an effort based HCR should be accompanied with effort models restricted by effort based advice in the biological OM.

Available HCRs can be divided into two groups depending on the input data used to generate the advice, stock status indicators (*model-based* HCR) or abundance indices obtained through scientific surveys or statistical analysis of fishery depended data (*model-free* HCR).

The HCRs are briefly described in Table 2.1 and detailed information about them can be found in the references given there. All the HCRs generate a TAC advice and for all of them, except for the Bay of Biscay anchovy one, the TAC for year y is given based on the *perceived* population up to year $y-2$. The same happens in reality where in year $y-1$, when the TAC advice for year y is calculated, only data up to year $y-2$ is available. The *perceived* population can refer to either an stock or an abundance index depending on the type of the HCR. In the case of Bay of Biscay anchovy HCR, the stock was managed in the middle of the year and the TAC for year y was given based on *perceived* population in the same year.

Table 2.1: List of some of the HCRs implemented in FLBEIA. The reference points used in each HCR are specific of the HCR itself and has not been defined here, see the reference cited for detailed information.

Type	Name	Input	Ref.Points	Description	Reference
Model Based	AnnualHCR	*Perceived* stock(s) in year y	Case specific	The targets and the constraints are defined by the user in each specific model implementation.	Flash library in www.flr-project.org
	IcesMSY		F_{msy}, $B_{lim}, B_{trigger}$	The objective is that fishing mortality, F, equals F_{msy}. If spawning stock biomass, SSB is above $B_{trigger}$, TAC advice corresponds with an F equal to F_{msy}, if $B_{lim} \leq SSB \leq B_{trigger}$ F is reduced linearly and if $SSB \leq B_{lim}$ TAC advice is zero.	ICES (2012)
	froeseHCR		B_{msy}, MSY, τ_0, τ_1, τ_2	The objective is that the SSB is above B_{msy}. If $SSB \geq \tau_2 \cdot B_{msy}$ TAC advice is equal to $\tau_0 \cdot MSY$. If $\tau_1 \cdot B_{msy} \leq SSB \leq \tau_2 \cdot B_{msy}$ TAC advice is reduced linearly and if $SSB \leq \tau_1 \cdot B_{msy}$ TAC advice is zero.	Froese et al. (2011)
	aneHCR		$\tau_0, \tau_1, B_{trig1}$, B_{trig2}, B_{trig3}, TAC_{max}, TAC_{min}	TAC is allowed to increase linearly as the biomass increases, from TAC_{min} up to reaching TAC_{max} at B_{trig3}. If $B_{trig2} < SSB \leq B_{trig3}$ TAC is set at $\tau_0 + \tau_1 \cdot SSB$ and if $SSB \leq B_{trig1}$ TAC advice is zero	STECF (2014)
	MultiStockHCR		F_{msy}, F_{low}, F_{upp}, $B_{lim}, B_{trigger}$	The HCR is applied simultaneously to a set of stocks varying their fishing mortality in the same degree and with the objective of producing a fishing mortality advice within the range (F_{low}, F_{upp}) for all of them.	Garcia et al. (2019b)
Model free	annexIVHCR	$id_{y-6}, \cdots, id_{y-2}$	τ_0, τ_1	The average of the indices in years $y-6, y-5, y-4$ is compared with that in years $y-3, y-2$, if the difference is higher than τ_0% the TAC is varied in a τ_1%. If not the TAC is maintained constant or is changed linearly.	ICES (2010)
	ghlHCR	$\{id_{jk}\}_{j \in \{1,2,3\}, k \in y-6, \cdots, y-2}$	τ_0, τ_1, τ_2	A linear model is applied to each index, the TAC is changed in a τ_0% depending on the average of the slopes in the linear models in comparison with τ_1 and τ_2.	NAFO (2010)
	pidHCR	$id_{y-6}, \cdots, id_{y-2}$	K_p, K_i, K_d, τ	The HCR has 3 parts, the Proportional, the Integral and the Derivative (PID) which weight is controlled with K_p, K_i and K_d. The variation in the TAC is equal to the weighted sum of the PID parts and it is constrained by τ.	Pomarede et al. (2010)
	littleHCR	id_{y-3}, id_{y-2}	C_{tg}, I_{lim}, I_{tg}	The objective is that the abundance index equals the target I_{tg}, in which case TAC advice is C_{tg}. Otherwise, TAC advice is adjusted linearly taking into account the distance to I_{lim} and I_{tg}. Below I_{lim} TAC advice is zero.	Little et al. (2011)

2.2.3 Model Initialisation

To initialise the model two types of data are needed, historical data (starting conditions) and model parameters in the projection. For each stock the historical period should include at least as many years as the age at recruitment so the spawning stock biomass that will produce the recruitment of the first year of the simulation can be calculated from the historical data. Furthemore, if the assessment model or the HCR depend on the historical period, then the historical data should include at least this time period, otherwise, just one year to start the simulation would be enough.

The uncertainty in the simulation is introduced using Monte Carlo simulation. The model runs independently in each model replicate and in each replicate the values of the input factors are changed. Each input factor can be conditioned using a single value or a vector, in this last case each replicate in the Monte Carlo simulation is conditioned taken a single value from this vector each time.

In theory, `FLBEIA` supports unlimited number of stocks, fleets, metiers, covariates and replicates. In practice, memory allocation in the operating system could set the limit.

2.3 Validation and Verification of `FLBEIA`

Along the development process of `FLBEIA` and its use in different case studies, the model has been verified and validated by different users employing different techniques. The application of the model in practical cases has been an essential part in the validation of the model. It has allowed to ensure that the coding is free of bugs and that it behaves as expected. Based on the terminology used by Balci (1997), below we explain which of the techniques listed there have been used, and how, along time.

Modularity The model has been developed modularly, which facilitates the verification of the model (Kleijnen 1995, Sargent 2011). Each of the functions (modules) that built up the model has been tested individually to check that it behaves as intended and produces the correct answer.

Face validity The implementation of `FLBEIA` presented in Chapter 4 of this thesis has been build in colaboration with stakeholders from the fishing sector in the framework of the MyFish European project http://www.myfishproject.eu/. The fishermen face validated the model in dedicated sessions. In these sessions the model was presented together with the main assumptions and the data used. The assumptions and results were discussed and improvements to the model configuration and new management scenarios were suggested. The suggestions and new scenarios were considered and the new results were presented again to them. The model results have been presented to stakeholders in other model implementatins too.

Documentation checking `FLBEIA` has an extend documentation:

- `R`-help pages,
- Scientific paper describing the model (Garcia et al. 2017a),
- User manual which latest version is available within the `R` package.
- Set of thematic tutorials dedicated to different aspects of model set up and of fisheries management. They can be find in `www.flr-project.org`.

This documentation is routinely revised by the `FLBEIA` development team to ensure it is up to date and it is compatible with the lasts developments.

Inspection The model was inspected by a group of fisheries scientist experts with different expertises. The inspection consisted on the presentation of the model with the main assumptions, comparison with other modelling approaches and the implementation of an specific case study. The group made several suggestions for the improvement of the model that were later on included in the development process. A detailed report of the meeting is avaible in Jardim et al. (2013).

Structural Analysis The control flow chart of `FLBEIA` in Figure 2.3 was designed to show the model structure and steps followed in the simulation.

Assertion Checking In the model development process notifications are used within many of the functions to ensure that the model behaves as expected.

Beta Testing The beta testing has not been carried out officially but the model has been tested by several experts outside the development team and they routinely report bugs, through email or github, and unexpected results are discussed to ensure their adequacy.

Bottom-up Testing The model has been developed using a bottom-up approach and as indicated before each of the modules was independently tested. Furthermore, the individual modules were then assembled and further tested as the model was put together.

Comparison Testing `FLBEIA` was used to produce mixed fisheries advice for Iberian Waters in the ICES mixed fisheries working group (ICES 2018a). The results obtained with `FLBEIA` were compared with those obtained in the short-term forecast carried out in the single stock assessment working groups to ensure that both models were consistent and provide the same answer in a single stock basis.

Debugging The model has been extensively debugged to correct bugs and to ensure that the model behaves adequately in all the steps.

Execution tracing As the simulation progresses several messages are printed in the screen with the values obtained in specific processes.

2.4 Discussion

`FLBEIA` provides a model to conduct integrated bio-economic impact assessment of a wide range of management strategies. It allows simulating the two most used structures in fish population dynamics modelling, age and biomass. Regarding fleets, it includes several functions to model their long- and short-term dynamics. Moreover, there is a covariates module that can incorporate variables of interest not present in biological and economic components. This module can be used, for example, to simulate the abundance of non-commercial species or environmental factors which interact with the abundance of some of the stocks in the biological OM. The MP describes an annual management process and the management advice can take place in any season. In addition, the management can incorporate measures such as changes in gear selectivity, temporal closures or capacity restrictions.

`FLBEIA` complements the already existing integrated bio-economic impact assessment models (BIOMAS, IAM, Fishrent,...). The strengths of `FLBEIA` are that the MP is modelled explicitly, it is composable and uses `FLR` libraries. Furthermore, the MP in `FLBEIA` does not only include the HCR as occurs in many simulation models (for example all those cited in the introduction), but it also includes the observation and assessment models. The composability of the model allows different functions to be selected to describe each of the processes that build up the fishery system and to introduce new models to satisfy specific user requirements. The functions implemented correspond with already published models and their implementation in `R` has been individually tested to avoid coding bugs. Furthermore, the assembly of the models has also been tested following a bottom-up approach. `FLR` libraries have contributors across a number of laboratories and universities and hence `FLBEIA` can automatically benefit from new developments in `FLR`. Furthermore, as `FLR` is being used in a large number of case studies and the input data structures in `FLR` are standard, the data used in these specific cases can be directly used to feed `FLBEIA`.

Trophic interactions are a crucial step when moving from single stock based fisheries management to ecosystem based fisheries management. Hilborn (2011) and Punt et al. (2016) recommend the incorporation of trophic interactions in the OM in a set of best practice guidelines in MSE. At present, none of the models in `FLBEIA` includes trophic relationships and stock interactions come about mainly through fleets' catch. At stock level, there is a stock-recruitment relationship which includes the abundance of a different stock as a covariate. However, the structure of `FLBEIA` allows trophic interactions to be incorporated by adding the adequate functions in the biological and covariates OM. For example, a new population dynamics model could be coded where the natural mortality of preys would be updated by a function dependent on predators' abundance before the survival equation is applied in the biological OM. On the other hand, there is a prototype that links Gadget multi-species model (Begley 2004, Howell and Bogstad 2010) with `FLBEIA`. This will allow to use all the flexibility of Gadget in the OM of `FLBEIA`, with throphic interactions and a length structure in the fish stocks, and combine it with the other `FLBEIA` components.

The fleets dynamics are a key source of uncertainty in fisheries management (Fulton et al. 2011b). However, there are no fleet dynamics models that are generally accepted, as it happens with population dynamics models, where production models, exponential survival model in age structured populations or specific stock recruitment models (Quinn and Deriso 1999) are well endorsed by fishery scientists. A review of fleet dynamics models can be found in van Putten et al. (2012) (short- and long-term) and Nøstbakken et al. (2011) (only long-term). The wide range of possibilities to describe the dynamic of the fleets makes it difficult to develop integrated bio-economic models that can be used in a wide range of case studies. `FLBEIA` does not provide a general solution to the incorporation of fleet dynamics models in the MSE framework, but it allows new fleet dynamics models to be incorporated to fulfil case specific requirements. In particular `FLBEIA` provides four short-term fleet dynamics models. In the first one al the parameters are given as input data and serves for example to test different effort management scenarios. A second one describes the dynamic of sequential fisheries and the other two describe the dynamic of mixed fisheries fleets. The two mixed fisheries dynamics models are governed by opposite principles, whereas in the Fcube like approach (Ulrich et al. 2012) the dynamic of the fleet is driven by the inertia of the system (effort distribution along metiers is commonly conditioned using historic data), in the profit maximization approach effort distribution is driven by the economic performance of the fleet. The idea that fishermen follow a purely profit maximization approach is controversial (Salas and Gaertner 2004). For example, tradition (Marchal et al. 2013) or inertia (Prellezo et al. 2009) have been demonstrated to be more important than economic performance in some cases. Probably, the true dynamic of the fleets are somewhere between both approaches and a fleet dynamics model that mixes both approaches could represent better the dynamic of mixed fisheries as it was done in (Marchal et al. 2013). However, in `FLBEIA` it is not straightforward to build a model that mixes both approaches. The reason is that apart of having a different distribution of effort along metiers they also have a different total effort. A possible solution would be modifying the profit maximization function to incorporate an additional parameter, which penalizes the departure from the historical effort distribution and calibrate it using historical data.

Fishing effort allocation is highly dependent on spatial dimension (Pelletier and Mahévas 2005) and area based management is being increasingly used (Hilborn 2011). In principle, both require spatial models in order to be included into simulations. However, these types of models only make a difference when there is time dependent stock movement. Otherwise, fleets' spatial allocation or area based management could be simulated implicitly through metiers associated with determined areas and metier specific stock catchabilities. Closing an area would mean to cancel the catchability or effort share of the metiers associated to this area. Stock movements between areas are not normally known. Thus, in most cases, tools that are not spatially explicit, such as `FLBEIA`, could be valid to conduct impact assessments of spatial fleets' dynamics or management. In DAMARA project the closure of an area was evaluated using this approach (EC 2016).

The management procedure focuses on the North East Atlantic management procedure which principal characteristic is the annual TAC advice (Daw and Gray 2005). This approach is followed in many cases elsewhere, but is not currently applicable, for example, in the Mediterranean Sea, where most of the stocks are managed using effort restrictions. In order to incorporate such a management into `FLBEIA`, as we mentioned above, effort based HCR and fleet dynamics models restricted by effort advice should be implemented. Individual transferable quotas are increasingly used as a fisheries management tool (Beddington et al. 2007). Such a system could be implementable in `FLBEIA`, but it would require the simulation of a catch quota market which, in each year of the simulation, updates quota shares of the fleets for each of the stocks. In `FLBEIA` it would imply the incorporation of an additional module within the fleets OM which updates the quota shares at fleet level before they are used in the short-term dynamics module.

In summary, `FLBEIA` is a flexible and extendible model which can be used to carry out bio-economic impact assessment of a wide range of management strategies in diverse case studies. Besides, specific model implementations can incorporate social and environmental variables into the simulation. Thus, it can be categorized as a model of intermediate complexity for ecosystem assessments (Plagányi et al. 2014), half way between simple bio-economic models and full ecosystem models such as Atlantis (Fulton et al. 2005; 2004) or Ecosim with Ecopath (Christensen and Pauly 2004). The model is composable and the complexity of specific model implementations is determined by the user choices.

MSE has been postulate as an appropriate tool to engage stakeholders in the modelling and decision making processes of fisheries management. In this respect, the composable nature of `FLBEIA` makes it a suitable model to be used in participatory modelling or participatory decision analysis process (Voinov and Bousquet 2010).

Conditioning this kind of complex models is out of the scope of most of the stakeholders. However, once the model is conditioned running it and analysing the results by non-experts could be achievable. Future developments of `FLBEIA` will be focused on providing a platform to run the model and analyse the results once the model is conditioned. The implementation of new models to describe the dynamic of the processes that build up `FLBEIA`, such as trophic interactions or new fleet dynamics models, will be driven by the work in specific case studies.

Chapter 3

Global sensitivity analysis

The criteria defined and the guidelines proposed in this chapter have been presented and published in the following forums:

- *The criteria and the evaluation of their performance in* ***Environmental Modelling & Software*** *journal: "Robust combination of the Morris and Sobol methods in complex multidimensional models"*
- *The criteria, the guidelines and the potential of using GSA in MSE simulation models in the* ***Ninth International Conference on Sensitivity Analysis of Model Output****: "Global sensitivity analysis of fishery management simulation models: Efficient conditioning and Robust combination of the Morris and Sobol methods"*
- *The criteria and the guidelines in the* ***XVII Conferencia Española y VII Encuentro Iberoamericano de Biometría****: "Global Sensitivity Analysis of complex models: Combining Morris and Sobol methods in a robust way"*

3.1 Introduction

GSA consist on explaining the variability in the output of the models through the variability in the input factors. This approach has been postulated by many authors as a key ingredient in the validation process of simulation models (Saltelli et al. 2000).

Nowadays there exist a variety of methods to conduct GSA (see Pianosi et al. (2016), Plischke (2016) or Norton (2015) for recent reviews on existing methods and practices). The available methods range from qualitative methods, like scatterplots, to the most complex variance decomposition methods. In the last group, the Sobol variance decomposition method (Sobol 1993), is considered the reference method by many authors (Confalonieri et al. 2010, Homma and Saltelli 1996, Sarrazin et al. 2016, Yang 2011).

The methods can be characterized by:

- Their ability to cope with non-linearities.
- Their ability to cope with interactions.
- The way the sampling is defined in the experimental design, using probability distributions or a finite number of levels defined in the domain of existence of each input factor.
- The number of model runs needed to obtain a reliable output (the cost of the analysis).
- The type of output generated (plots, a ranking of the input factors or estimates of the sensitivity indices).
- How do they characterize the uncertainty (usually using the output variance but also using the whole probability distribution).

One of the main drawbacks of the Sobol variance decomposition method is its high computational cost. The cost depends on the number of input factors and the CPU time needed to run one instance of the model. In simulation models with tens of input factors and model execution time of several minutes the computational cost of the analysis could be unaffordable. Fisheries management simulation models like `FLBEIA` usually belong to this category with many input factors and significant execution time. Furthermore, the number of iterations needed for the methods to converge is not known. Saltelli et al. (2008) give a rough approximation for some of the methods. However, Sarrazin et al. (2016) found out that the number of model iterations needed by the methods to converge are higher.

One alternative, for computationally intensive models, is to use emulators or metamodels to approximate the original model (Coutts and Yokomizo 2014, Ratto et al. 2012). The metamodels should be simpler and computationally less intensive models from which sensitivity indices can be calculated easily. Other alternative is to combine variance decomposition methods with a screening method to reduce the number of input factors (Saltelli et al. 2008). First, the most important input factors are identified with the screening method and then the variance decomposition is applied only to those input factors, fixing the rest of the factors to any value in their existence domain. The most popular screening method is the Morris elementary effect method (Morris 1991).

When a variance decomposition method is combined with a screening method it is essential that the factors identified by the screening method are really the most important ones. The selection of the input factors need to be accurate and the method need to have converged. In the Morris screening method there is no quantitative method to select the most important factors, a *visual* selection is used instead. This is not a big problem when there is only one output variable. However, when the output is multivariate, maintaining the same selection criterion along all the output variables is usually difficult. Even more, it is not possible to carry out a bootstrap simulation to assess convergence using a *visual* criterion. The most common approach is to select a fixed number of factors for each output variable (DeJonge et al. 2012, Hussein et al. 2011, Morris et al. 2014). Alternatively, Campolongo et al. (2007) proposed to use *Savage* scores (Savage 1956). Regarding convergence, Sarrazin et al. (2016) proposed several convergence criteria to assess the convergence of GSA methods. The criteria defined there are specific to the objective of the analysis. However, none of the objectives was to identify the input factors that should enter into the variance decomposition method after the application of an screening method. If applied for this purpose they could lead to a computational surcharge.

On the other hand, although GSA seems a natural complement of MSE, none of the fisheries simulation models combined with a GSA found in the literature review followed the MSE approach strictly. For the case of the most complex full ecosystem models, Fulton (2010) and Plagangy (2007) stated that performing a GSA is not feasible. We believe that the infrequent application of GSA to MSE simulation models is due to:

- the complexity of the models, which inhibits the use of the available GSA software,
- the high computational cost, and
- the lack of practical applications in the field.

MSE models like `FLBEIA` are characterized by including many correlated input factors, a multivariate output, simulating the management process explicitly, and being computationally intensive.

Thus, the objective of this chapter is to define a scientifically sound and computationally efficient methodology to apply GSA to complex fishery MSE models. We approach the problem of reducing the computational cost from two directions: we propose reducing the number of effective factors in the GSA by conditioning the model efficiently and introduce new selection and convergence criteria for a robust selection of the input factors in the Morris method. While the selection criterion removes the subjectivity from the screening process, the convergence criterion ensures that the procedure has converged to select the most important factors. Additionally, we propose some guidelines to facilitate GSA of MSE simulation models.

This chapter is organized as follows, first the Morris elementary effect method is presented. In the next two sections the selection and convergence criteria proposed in this thesis for the Morris method are presented. In the third section, the Sobol variance decomposition method is described; the derivation of sensitivity indices and how to estimate them numerically, and the sensitivity indices for multivariate output. Then, the performance indicators to compare the efficiency of several selection criteria in the Morris method are defined. Finally, a set of guidelines to facilitate the application of GSA to fisheries management simulation models are proposed.

3.2 The elementary effects method

Morris introduced the elementary effects method in 1991 (Morris 1991) and other authors developed it further (Campolongo et al. 2007; 2011, Ruano et al. 2012). It is an effective mean of identifying important input factors at a lower computational cost than the Sobol method (Saltelli et al. 2008). Campolongo et al. (2007) improved the method's convergence through more efficient sampling of the input space. Furthermore, they developed an expression that allows grouping input factors and treat them as if they were a single input factor, with the subsequent reduction in computational cost. Extension of the methods of Campolongo et al. (2007) and criticism of their examples appeared in Norton (2009).

The method consists of evaluating the simulation model, φ, along a set of trajectories, $\mathbb{P}$, defined in the unit hypercube, $\omega = [0,1]^K$, where K corresponds with the number of input factors. The intervals in $[0,1]$ are divided in subintervals of with Δ and the trajectories are defined throughout the bounds of the subintervals. When the existence domain of the model is different to the unit hypercube, the trajectories are transformed into the model's original domain, Ω, using a transformation function. The absolute elementary effect for each trajectory p in $\mathbb{P}$, AEE_p, is calculated for each input factor X_k, for $k \in \{1,...,K\}$. For simplicity of notation, we will omit the k subscript for the input factor whenever it is not necessary in the context. Therefore, the AEE_p for trajectory p and input factor X_k is defined as:

$$\mathrm{AEE}_{p,X_k}(\boldsymbol{X}) = \frac{|\varphi(\boldsymbol{X}) - \varphi(\boldsymbol{X'})|}{\Delta}$$

where φ denotes the simulation model, $\varphi(\boldsymbol{X}) = \boldsymbol{Y}$ and $\boldsymbol{Y} = (Y_1, \ldots, Y_J)$ represents the output of the model, J denotes the number of output variables, $\boldsymbol{X}$ and $\boldsymbol{X'}$ are two consecutive points in the trajectory p that differ only in the value of X_k. Finally, the AEE of the input factor X_k, AEE_{X_k}, is equal to the mean of the AEE_p-s along all the trajectories:

$$\text{AEE}_{X_k} = \frac{\sum\limits_{p \in \mathbb{P}} \text{AEE}_{p,X_k}}{R} \quad : \quad k \in \{1, \ldots, K\} \tag{3.1}$$

where R denotes the cardinality of $\mathbb{P}$. The AEE-s are calculated for each output variable. Hence, for each input factor X_k there is a set of AEE-s $\{AEE_{X_k,Y_j}\}_{j=1}^{j=J}$, where j is the subscript for the output variable. For simplicity of notation, we will omit the j subscript for the output variable whenever it is not necessary in the context.

The following subsections present the calibrated visual criterion to select the most important input factors and the convergence criterion for the Morris method.

3.2.1 The calibrated visual criterion

First, we define three selection criteria that jointly provide mathematical sense to the criterion used in the visual selection. To give a closed expression for the three criteria, for each output variable Y, we order the input factors according to their AEE value, i.e., $\text{AEE}_{X_1,Y} \leq \text{AEE}_{X_2,Y} \leq \ldots \leq \text{AEE}_{X_K,Y}$ and define $\mathbb{F}$ as the set of all the input factors.

1. *Fixed number of factors*: the selected input factors are those that verify that their AEE are among the δ_{F} input factors with the highest AEE for at least one output variable Y_{j_0}. The set of selected input factors is denoted as $\mathbb{F}_{\text{F}}$ and it is defined as,

$$\mathbb{F}_{\text{F}} = \Big\{ X \in \mathbb{F} : \exists\, j_0 \in \{1, \ldots, J\} \text{ s.t. } \text{AEE}_{X,Y_{j_0}} > \text{AEE}_{X_{K-\delta_{\text{F}}},Y_{j_0}} \Big\}$$

2. *Factors with high AEE value*: the selected input factors are those that verify that their AEE is higher than a proportion, δ_{H}, of the maximum value of all the AEE-s for at least one output variable Y_{j_0}. The set of selected input factors is denoted as $\mathbb{F}_{\text{H}}$ and it is defined as,

$$\mathbb{F}_{\text{H}} = \Big\{ X \in \mathbb{F} : \exists\, j_0 \in \{1, \ldots, J\} \text{ s.t. } \text{AEE}_{X,Y_{j_0}} \geq \delta_{\text{H}} \cdot \max\{\text{AEE}_{X_k,Y_{j_0}}\}_{k=1}^{K} \Big\}$$

3. *Factors distinguished from the others*: the selected input factors are those that verify that the difference between all the consecutive AEE-s is higher than a proportion δ_{D}, for all the AEE-s with a higher AEE than the input factor itself, for at least one output variable Y_{j0}. The set of selected input factors is denoted by $\mathbb{F}_{\mathrm{D}}$ and it is defined as:

$$\mathbb{F}_{\mathrm{D}} = \Bigg\{ X \in \mathbb{F} : \exists j_0 \in \{1, \ldots, J\} \text{ s.t.} \\ \frac{\mathrm{AEE}_{X_k, Y_{j0}} - \mathrm{AEE}_{X_{k-1}, Y_{j0}}}{\mathrm{AEE}_{X_K, Y_{j0}}} \geq \delta_{\mathrm{D}},\ \forall X_k : \mathrm{AEE}_{X_k, Y_{j0}} > \mathrm{AEE}_{X, Y_{j0}} \Bigg\}$$

Then, given $\mathbb{P}$ a set of trajectories along ω and $K_{EE} < K$ the number of input factors we intend to enter into the Sobol method, the calibrated visual criterion is defined as the weighting of the three criteria defined above and it is applied as follows.

1. Evaluate the model at the points that form the trajectories in $\mathbb{P}$ and calculate the $\{AEE_{X_k,Y_j}\}_{k=1}^{K}$ for all $j \in \{1, \ldots, J\}$ using (3.1).
2. Find the parameters δ_{F}, δ_{H}, and δ_{D} that result in the selection of K_{EE} input factors. With the *fixed number of factors* criterion, it may be impossible to select exactly K_{EE} input factors, in which case δ_{F} is selected as the minimum number of input factors that results in selecting a total number of input factors equal or bigger than K_{EE}.
3. To support calibration of the selection criterion, conduct a *visual* selection of the input factors. A set of input factors is selected for each output variable and the resulting sets are then merged in a single set $\mathbb{F}_{\mathrm{V}}$. The selection is done in such a way that the cardinality of $\mathbb{F}_{\mathrm{V}}$ is equal to K_{EE}.
4. Apply the weighted criterion for the three previously defined criteria using different combination of weights. Firstly, define a three dimensional set of values that provide a good coverage of the unit hypercube. Secondly, for each triplet in the set of weights and each output variable, the number of input factors selected is equal to the weighted mean of those selected with each of the three criteria. Finally, once the number of input factors to be selected for each triplet is decided, the ones with the highest AEE are selected. Then, the set of input factors that corresponds to each triplet of weights, $\mathbb{F}_{\mathrm{W}}$, is formed by the union of the sets of input factors selected for each output variable.

5. For each triplet compare the corresponding set of input factors calculated in the previous step, $\mathbb{F}_{\mathrm{W}}$, with $\mathbb{F}_{\mathrm{V}}$. Then, identify the weights, $w_{\mathrm{F}}, w_{\mathrm{H}}$ and w_{D} that produce the largest intersection between both sets and among those select the triplet that produces the smallest cardinal of $\mathbb{F}_{\mathrm{W}}$.

Thus, we obtain a procedure that uses the same criterion for the selection of input factors in all the output variables. Furthermore, the input factors selected with this procedure highly agree with the visually selected ones.

3.2.2 Convergence criterion

We consider that the Morris method has converged when the input factors identified as the most important do not change when the cardinal of $\mathbb{P}$ is increased. We assess convergence using bootstrapping and the selection criterion defined previously.

First, we generate randomly a sufficiently large set of trajectories, $\mathbb{P}$, with cardinal R. Then, using the method in Campolongo et al. (2007) we find the set of trajectories $\mathbb{P}_r$ for different values of r such that $r < R$. In particular, for each i and l such that $r_i < r_l$, once AEE-s are calculated for $\mathbb{P}_{r_i}$, we need only to evaluate the model in the trajectories that are not included in $\mathbb{P}_{r_i}$ in order to calculate AEE-s for $\mathbb{P}_{r_l}$.

For each r, we perform the bootstrap in three steps using N_{boot} iterations:

1. Apply the calibrated visual criterion to $\mathbb{P}_r$ to obtain the weights, w_{F}, w_{H}, w_{D} as proposed for the calibrated visual criterion.
2. Sample with replacement r trajectories from the original set $\mathbb{P}_r$.
3. Find the value of the parameters δ_{F}, δ_{H}, and δ_{D} as proposed for the calibrated visual criterion.
4. Apply the calibrated visual criterion to that sample using the set of parameters $\{w_{\mathrm{F}}, w_{\mathrm{H}}, w_{\mathrm{D}}, \delta_{\mathrm{F}}, \delta_{\mathrm{H}}, \delta_{\mathrm{D}}\}$ obtained in previous steps.
5. Repeat steps 2 to 4 N_{boot} times.

To assess convergence, we define the indicator m_X^r for each r and each input factor X:

$$m_X^r = \sum_{h=1}^{N_{\mathrm{boot}}} \pi_X^r(h)$$

where π_X^r is equal to 1 if input factor X has been selected in iteration h, and 0 otherwise. If an input factor is selected in all the bootstrap iterations, i.e., if $m_X^r = N_{\mathrm{boot}}$, the input factor is among the most relevant ones. Therefore, to identify the K_{EE} most important input factors, it would be sufficient to increase the number of trajectories r until K_{EE} input factors are selected in all the bootstrap iterations.

However, this condition could be very demanding, and therefore, the criterion can be relaxed using a proportion ν of N_{boot}. We define $\mathbb{F}_r$ as the set of input factors selected in, at least, $\nu \cdot N_{boot}$ bootstrap iterations when r trajectories are used:

$$\mathbb{F}_r = \{X \in \mathbb{F} : m_X^r \geq \nu \cdot N_{boot}\}$$

If K_r is the cardinality of $\mathbb{F}_r$, K_r increases with r and we consider that the process has converged when $\exists\ r_0 \leq R$ such that:

$$K_{r_0} = K_{r_0+1} = \ldots = K_{r_{\max}}$$

In general $K_{r_{\max}}$ is lower than K_{EE} because the number of input factors selected in each bootstrap iteration are constrained to result in the selection of K_{EE} input factors. Hence, in general, those selected in $\nu \cdot N_{boot}$ bootstrap iterations will be equal or lower than K_{EE}.

When convergence has been achieved for the number of input factors to be selected, we define three criteria to select the input factors to be considered when applying the Sobol method, $\mathbb{F}_{\mathrm{M}}$.

The set of input factors selected with the maximum r, $r_{\max}$, used in the application of the Morris method:

$$\mathbb{F}_{\mathrm{M}} = \mathbb{F}_{r_{\max}}$$

The union:

$$\mathbb{F}_{\mathrm{M}} = \bigcup_{r=r_0}^{r_{\max}} \mathbb{F}_r$$

The intersection:

$$\mathbb{F}_{\mathrm{M}} = \bigcap_{r=r_0}^{r_{\max}} \mathbb{F}_r$$

The three criteria yield a different number of selected input factors, because in the tail of the distribution the AEEs of some input factors go in and out of $\mathbb{F}_r$. In terms of selecting a smaller number of input factors, the most restrictive option is the third, whereas the second is the most conservative, and the first is intermediate. As a general procedure, we can examine the degree of difference between the three options in terms of the set of selected input factors.

Figure 3.1 shows the application of the whole proposal including the two criteria, the calibrated visual criterion for selection and the bootstrap for convergence.

3.3 Variance decomposiotion method

Sobol variance decomposition method is based on the decomposition of the output variance as a function of the variance of conditional expectations of the model output on the input factors (Sobol 1993).

Sobol (1993) proved that any square integrable function $\varphi(\boldsymbol{X}) = Y$ in $\Omega = [0,1]^K$ can be decomposed as:

$$\varphi(\boldsymbol{X}) = \varphi_0 + \sum_i \varphi_i(X_i) + \sum_{i<j} \varphi_{ij}(X_i, X_j) + \ldots + \varphi_{12\ldots K}(X_1, \ldots, X_k) \tag{3.2}$$

where each individual term is also square integrable and depends solely on the input factors corresponding with its index. This expansion is called high dimensional model representation. Furthermore, if the terms in the equation above have zero mean (i.e the integral of each term over each of the variables is zero), the terms in (3.2) are orthogonal and can be calculated using the conditional expectations of the model output. Mathematically:

$$\varphi_0 = \int \varphi(\boldsymbol{X}) d\boldsymbol{X} = E(\boldsymbol{X}) \tag{3.3a}$$

$$\varphi_i(X_i) = \int \varphi(\boldsymbol{X}) \prod_{k \neq i} dX_k - \varphi_0 = E(Y|X_i) - E(\boldsymbol{X}) \tag{3.3b}$$

$$\begin{aligned} \varphi_{ij}(X_i, X_j) &= \int \varphi(\boldsymbol{X}) \prod_{k \neq i,j} dX_k - \varphi_i(X_i) - \varphi_j(X_j) - \varphi_0 \\ &= E(Y|X_i, X_j) - E(Y|X_i) - E(Y|X_j) - E(\boldsymbol{X}) \end{aligned} \tag{3.3c}$$

and so on. Now, if we square on both sides of (3.2), replacing the terms in the right hand side by the expression obtained in (3.3), and integrate over ω, we get:

$$\int \varphi^2(\boldsymbol{X}) d\boldsymbol{X} - \varphi_0 = \sum_{s=1}^{K} \sum_{i_1 < \ldots < i_s}^{K} \int \varphi^2_{i_1 \ldots i_s} dX_{i_1} \ldots dX_{i_s}$$

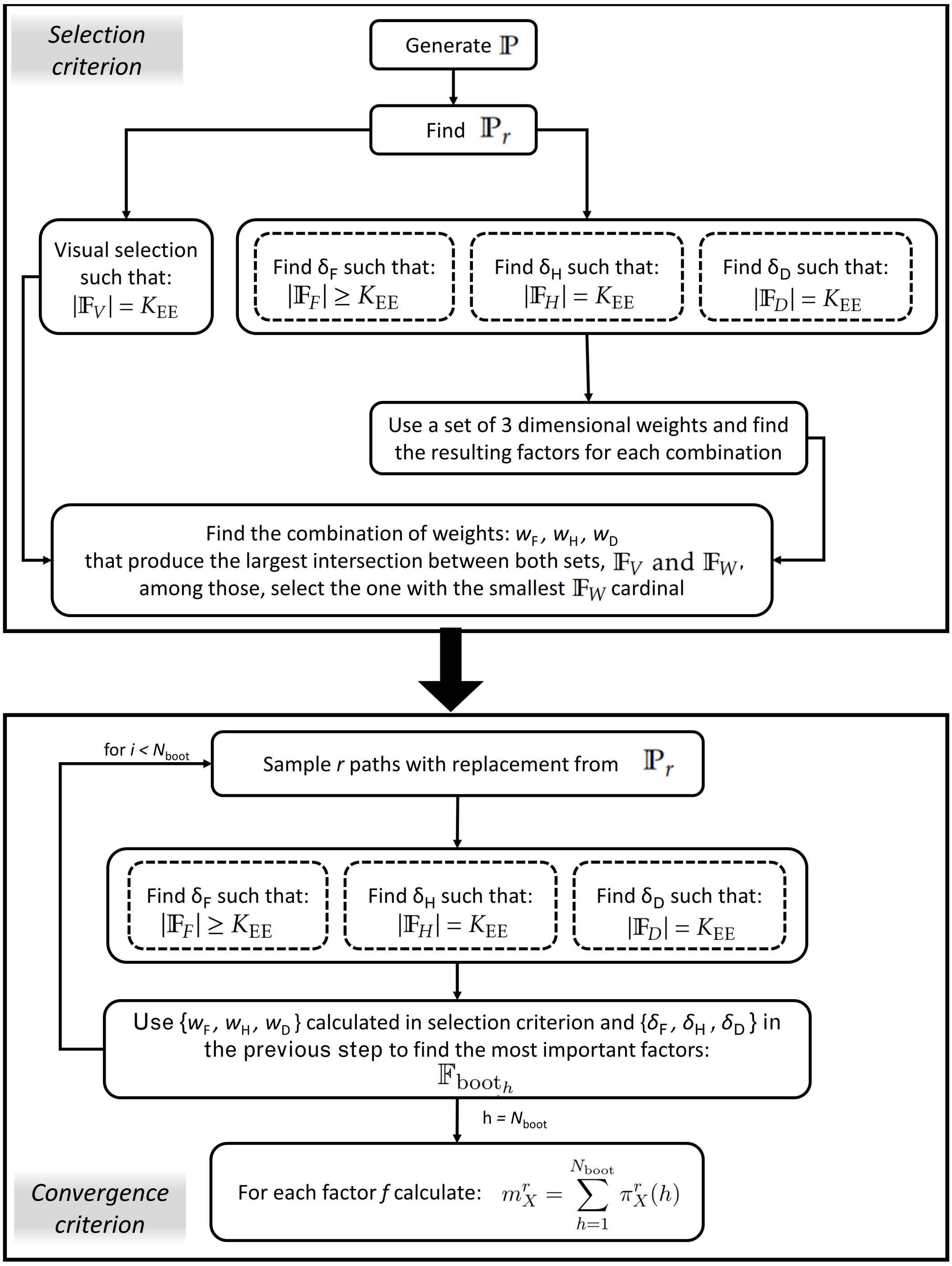

Figure 3.1: Steps for the application of the selection and the convergence criteria given $\mathbb{P}$ a set of trajectories and r the number of trajectories to use in the analysis. Figure taken from (Garcia et al. 2019a).

The constants:

$$V = \int \varphi^2(\boldsymbol{X})d\boldsymbol{X} - \varphi_0 \quad \text{and} \quad V_{i_1 \ldots i_s} = \int \varphi^2_{i_1 \ldots i_s} dX_{i_1} \ldots dX_{i_s}$$

correspond with the conditional variances of the model output on the input factor and:

$$V = \sum_{s=1}^{K} \sum_{i_1 < \ldots < i_s}^{K} V_{i_1 \ldots i_s}$$

In variance decomposition methods, the variance is used to characterize the variation in the output of simulation models. Hence, Sobol (1993) proposed to use the ratio between the conditional variances and the total variance as sensitivity measures, i.e:

$$S_{i_1,\ldots,i_s} = \frac{V_{i_1,\ldots,i_s}}{V}$$

Hence,

$$\sum_{s=1}^{K} \sum_{i_1 < \ldots < i_s}^{K} S_{i_1,\ldots,i_s} = 1$$

And,

$$\sum_{i=1}^{K} S_i = 1$$

means that the model is additive and there is no interaction between input factors. On the contrary, values much lower than 1 indicate that the model is highly non-linear.

In simple cases, the sensitivity indices can be calculated analytically. However, in most cases the models are too complex to allow the derivation of analytical expressions for the integrals in (3.3). For each of the sensitivity indices, the numerical approximation developed by Sobol (1993) requires evaluating the simulation model in a large set of Monte Carlo points. Hence, the computational cost of calculating all the terms in the decomposition (3.2) is equal to $N \cdot 2^K$, where K corresponds with the number of input factors and N with the base sample size that should be big enough to ensure the convergence of the method. Hence, the number of model evaluations required can be unapproachable even for relatively low number of factors.

As an alternative, Homma and Saltelli (1996) proposed summarizing the contribution of the input factors to the output variance using two sensitivity indices: *first-order* and *total-effect* indices. The first is equal to the ratio between the variance of the conditional expectation of the model output on k-th input factor and the total variance of the model output, mathematically:

$$S_k = \frac{V(E(Y|X_k))}{V(Y)} \tag{3.4}$$

where X_k denotes the k-th input factor, $Y = \varphi(\boldsymbol{X})$ is the unidimensional output of the simulation model represented by φ and $\boldsymbol{X} = (X_1, \ldots, X_K)$ represents the model input. This index represents the contribution of the k-th input factor to the output variance in isolation.

In turn, the *total-effect* is equal to the expected value of the conditional variance of the model output on all the input factors but one, the k-th input factor, denoted here as $\boldsymbol{X}_{\sim k}$. It represents the contribution to the variance of the k-th input factor alone and in combination with the remaining input factors. Mathematically it is written as:

$$S_{T_k} = \frac{E(V(Y|\boldsymbol{X}_{\sim k}))}{V(Y)} \tag{3.5}$$

In this way the decomposition of the output variance can be summarized using just two indices for each factor, the *first-order* and the *total-effect* sensitivity indices and the cost of the analysis is reduced to $N \cdot (K + 2)$.

3.3.1 Numerical calculation of the sensitivity indices

In this thesis we followed the numerical approximations proposed by Saltelli et al. (2010) which are based on the work by (Sobol 2001). Saltelli et al. (2010) compared different approaches for calculating the Sobol sensitivity indices using Monte Carlo simulations. Here, we have used the approach that was identified by the authors as the best in terms of convergence rate.

First, two independent matrices of dimension $N \times K_{\text{NG}}$ are constructed, A and B, the so-called *sample* and *re-sample* matrices, where N and K_{NG} are the number of base simulations and input factors of the model, respectively. The input factors can be multivariate, and therefore, K_{NG} can be larger than the number of effective input factors in the GSA, K. When the input factors are divided in groups, instead of considering every input factor alone, the elements in the Sobol decomposition that include this input factor represent the contribution to the variance of all the input factors in the group as a whole, in isolation in the case of *first-order* index, and in combination with other sets of input factors, in the case of the rest of the elements in the decomposition of variance. Hence, the input factors should be grouped sensibly to obtain meaningful results.

Second, additional K matrices, $\{A_k^B\}_{k\in 1,\dots,K}$, are constructed from the A and B matrices. Each A_k^B matrix is equal to A, except in the columns that correspond to the k-th input factor, which are taken from matrix B. If the k-th input factor is a group all the columns corresponding to this factor are replaced. Finally, the model is applied to each of the rows of A, B, and $\{A_k^B\}_{k\in 1,\dots,K}$ matrices. The numerator in (3.4) is then approximated by:

$$V(E(Y|X_k)) = \frac{1}{N}\sum_{i=1}^{N} \varphi(B_{i.}) \cdot \left(\varphi(A_{k,i.}^B) - \varphi(A_{i.})\right) \tag{3.6}$$

where $A_{i.}$, $B_{i.}$ and $A_{k,i.}^B$ denote the i-th row of matrices A, B, and A_k^B, respectively. In turn, the numerator in (3.5) is estimated as:

$$E(V(Y|\boldsymbol{X}_{\sim k})) = \frac{1}{2N}\sum_{i=1}^{N} \left(\varphi(A_{i.}) - \varphi(A_{k,i.}^B)\right)^2 \tag{3.7}$$

Finally, the total variance $V(Y)$ is approximated by:

$$V(Y) = \frac{1}{N}\sum_{i=1}^{N} \varphi(A_{i.})^2 - \left(\frac{1}{N}\sum_{i=1}^{N}\varphi(A_{i.})\right)^2$$

The convergence of the estimators can be assessed using the bootstrap confidence intervals' width (Sarrazin et al. 2016).

3.3.2 Global Sensitivity Analysis of Multivariate Output

The sensitivity indices introduced in the previous section are specific to unidimensional models. If the model were multidimensional, the sensitivity indices should be calculated independently for each of the dimensions. However, the same model evaluations could be used for their calculation. If the dimension of the output were high and the output variables were correlated summarizing the information obtained from the sensitivity indices could be very messy.

An alternative to the calculation of the sensitivity indices for each output variables is to use the generalized sensitivity indices (GSI) proposed by (Lamboni et al.

2011). These indices are the equivalent of the sensitivity indices defined in the previous section but for the overall variance of the output of a model with a multidimensional output. The generalized indices are based on the work of Campbell et al. (2006) who proposed to decompose the multivariate output using an orthogonal system and then apply the sensitivity indices individually to the most informative components. Lamboni et al. (2011) developed further the idea proposed by Campbell et al. (2006) and using principal component analysis as orthogonal decomposition, proved that the *first-order* and *total-effect* indices, (equations (3.6) and (3.7)), calculated on the sum of the principal components are to a multivariate output what the Sobol sensitivity indices are to the univariate one. The same model results used to calculate sensitivity indices are used in the calculation of generalized indices. Hence, their calculation do not imply any additional computational cost.

3.4 Performance of the selection criteria

Two performance indicators are defined to evaluate the performance of the *calibrated visual criterion* and other two selection criteria, the selection of a *fixed number of factors* for each output variable and the criterion based on *Savage* scores (Campolongo et al. 2007). The performance indicators are based on the *total-effect* indices calculated on the reduced simulation model obtained introducing variability exclusively in the K_{EE} input factors selected with the Morris method. The first performance indicator, uses the set of Sobol's *total-effect* sensitivity indices for each output variable Y_j, $\mathbb{S}_T^j = \{S_{T_k}^j\}_{k=1}^{K_{\mathrm{EE}}}$, to assess the performance of the criterion, where $S_{T_k}^j$ denotes the *total-effect* of the k-th input factor for output variable Y_j. In turn, the second one, the generalized performance indicator, uses the *generalized total-effect* indices for multivariate output defined by Lamboni et al. (2011), $\mathbb{G}_T = \{G_{T_k}\}_{k=1}^{K_{\mathrm{EE}}}$, where G_{T_k} denotes the *generalized total-effect* index of k-th input factor.

To assess the performance of the criterion under different conditions, the performance indicators are calculated for different sets of output variables and different number of input factors in the Morris method. Let us Z denote the number of input factors used in the fixed number of factors criterion to calculate the set of input factors in the Morris method. Then, the performance indicators are calculated as follows:

- The *fixed number of factors* criterion is applied to the Morris elementary effects selecting the Z input factors with the highest elementary effect value. The resulting number of selected input factors is denoted as $K_{\mathrm{EE,Z}}$.

- The *calibrated visual* criterion is applied using $K_{\mathrm{EE,Z}}$ number of input factors as threshold.
- The *Savage* criterion is applied selecting the $K_{\mathrm{EE,Z}}$ input factors with the highest score.
- For a given selection criterion, to calculate the performance indicator for output variable Y, first the corresponding *total-effect* values are assigned to the input factors selected in the application of the criterion, $\{X_1, \ldots, X_{K_{\mathrm{EE,Z}}}\}$, i.e :

$$\rho_k^j = \begin{cases} 0, & \text{if } X_k \notin \mathbb{F}_{\mathrm{M}}. \\ \frac{S_{T_k}^j}{\sum_{i=1}^{K_{\mathrm{EE}}} S_{T_i}^j}, & \text{otherwise.} \end{cases} \tag{3.8}$$

  where $S_{T_k}^j$ corresponds with the *total-effect* of input factor X_k for output variable Y_j. Then, the first performance indicator, Θ, is calculated as the ratio between the sum of all the ρ_k^j over all the input factors selected by the criterion and all the output variables $\{Y_1, \ldots, Y_J\}$. The sum is then divided by the number of output variables to place the possible values of the indicator between 0 and 1.

$$\Theta = \frac{1}{J} \sum_{j=1}^{J} \sum_{k=1}^{K_{\mathrm{EE},Z}} \rho_k^j \tag{3.9}$$

  The second performance indicator, the generalized indicator, Θ_G, is calculated similarly but instead of having one *total-effect* index per output variable Y, there is only one *total-effect* index for all the output variables. Hence, ρ depends only on the input factors and in (3.9) the sum along output variables and the division by the number of output variables disappear.

In the comparison of the three criteria the one with the highest Θ is the criterion which produces the best selection of input factors. Values of Θ equal to 1 indicate that the input factors selected by the criterion are the $K_{\mathrm{EE},Z}$ input factors in the top of the ranking, for all the output variables in the case of the first indicator, and for the ranking obtained with the *generalized total-effect* index in the case of generalized one. The procedure is not applied to $Z = 1$ because it implies to select δ_{H} and δ_{D} in such a way that only one input factor per output variable is selected, i.e., the three criteria are equivalent for $Z = 1$.

3.5 Guidelines

3.5.1 Vectors at age

Most fishery simulation models describe the stock dynamics using age structure in the population, implying that most input factors are multivariate with one value per age class. Furthermore, as the values at age are related with the growth process they are usually correlated. Hence, if all these values are considered in the GSA, as well as increasing enormously the number of factors, the correlation precludes using standard GSA techniques. The number of factors can be reduced and the correlation overcome by modelling the values at age as a function of uncorrelated parameters:

$$x_a = \Phi(a, \theta_1, \ldots, \theta_s, \epsilon) \quad : \quad s < n_a$$

where x_a denotes an observed value of the factor at age a, Φ the mathematical model, $\{\theta_i\}_{i=1}^{s}$ the model's parameters, ϵ the error term, and n_a the number of age classes. The parameters that enter into the GSA are $\{\theta_i\}_{i=1}^{s}$ and ϵ and they should be independent. If $\{\theta_i\}_{i=1}^{s}$ were correlated, some of the parameters could be modeled as a function of the others (see Section 5.2.1).

One of the most simple approaches to model vectors at age is quantile transformation. For each vector, random numbers sampled from a uniform distribution in $[0, 1]$ are transformed into the value of each age class using the inverse transformation method on the probability distribution of each value at age of the vector. This approach uses only one input factor corresponding with the sampling of the uniform distribution and maintains the correlation structure in the values at age. The resultant vectors at age with this method are translations of the original vector through the quantiles of their distribution (Figure 3.2), i.e., all the values in the vector corresponded to the same quantile. In the same figure, the curves obtained using an alternative model with two parameters is shown. In this case the input factors are the parameters of the model.

3.5.2 Grouping of variables

A common procedure to reduce computational cost of GSA is to group factors and then treat them as a single factor (Saltelli et al. 2008). In both, the Morris and Sobol methods, the factors within the same group are moved simultaneously but independently. In the Sobol method, the groups are included in matrices A and B as if they were single factors, but when A_k^B is generated the entire group is

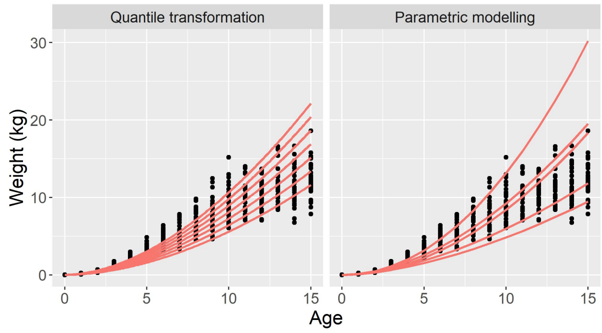

Figure 3.2: Two different means of modelling the uncertainty in the vectors at age. a) corresponds to quantile transformation and b) to a parametric modelization of the observed data.

interchanged. For the Morris method, Campolongo et al. (2007) developed the mathematical expression needed to calculate the AEE when groups are used.

Some set of factors are commonly used in most of the MSE implementations and they could be considered as a group, because the focus, in general, is on the impact of the entire set of input factors:

- The initial abundance at age of the stocks;
- The annual variability around the recruitment curve;
- The parameters of the stock-recruitment relationship;
- The annual observation error in total landings, total discards, or stock abundance;
- The aging error along year and ages. The aging error measures the probability of age a_i being assigned to an individual of age a_j. If the parameters are not grouped, this error implies $(n_a-1)^2$ individual factors if the error is considered time-invariant, and $(n_a-1)^2 \cdot n_y$ otherwise, where n_y denotes the number of years in the simulation (n_a-1 and not n_a, because they are proportions and the factors along age classes sum up to 1).

Note that when groups are used, the save on computational cost is attained at the cost of losing information. Hence, we need to be sure we are not interested in the effect of individual input factors within the group.

3.5.3 Observable variables in management procedure

The explicit simulation of the uncertainty in the MP renders MSE different from other simulation approaches. In MSE models aleatory and epistemic uncertainty can be separated accurately. The source of the aleatory uncertainty is the natural variability in the variables of the OM. In turn, the uncertainty in the MP has two components, that derived from the variability in the OM and that derived from a lack of knowledge of the system. The latter could be reduced through an increase in sampling and/or through further research, but not the former.

The variables in the MP correspond with the observation of variables in the OM. Thus, real and corresponding observed input factors are correlated; however, this can be avoided by introducing into the GSA the error term that relates the two variables instead of the observed variable itself. For each model replication, the values of the observable variables in the OM are generated as:

$$\chi_{OM_y} = \mu \cdot \xi_y$$

where μ denotes the mean value of the variable, ξ the natural variability, and y the year. If χ and μ are vectors at age, ξ can be either a scalar or a vector, depending if the observation error is age dependent or not.

Input factors sampled routinely are observed each year with observation and measurement error (Francis and Shotton 1997), i.e., for input factor χ:

$$\chi_{MP_y} = \chi_{OM_y} \cdot \varepsilon_y$$

where ε is the observation error term. The mean of the distribution of ε represents the bias in the observation of χ_{OM} and its coefficient of variation (CV) the precision. The two variabilities, ξ and ε, are independent and represent different sources of uncertainty, natural variability the first and observation error the second. Here, we use multiplicative errors, because in `FLBEIA` all the errors are multiplicative, but they could be additive.

The factors that are naturally variable but are assumed constant in the MP can be modeled as

$$\chi_{MP} = \mu \cdot \zeta \tag{3.10}$$

where ζ is a scalar that models the perception bias in χ_{OM}. The drawback is that the importance of observation errors in variable χ_{MP} cannot be directly assessed because the observation error, $\frac{\zeta}{\xi}$, cannot be included as a factor.

Moreover, the age structured variables can be subject to aging error, as described in Section 2.2.2.1 . They are introduced in $\vec{\chi}_{MP}$ using matrix multiplication, i.e.,

$$\vec{\chi}_{MP_y} = (\vec{\chi}_{OM_y} \cdot \zeta_y) \cdot \Lambda$$

where $\vec{\chi}$ denotes a vector with values at age of a given input factor.

3.5.4 Convergence of individual factors

The convergence of the sensitivity indices is factor-dependent. While the convergence for some factors is reached with a few iterations, others require many iterations to converge. Furthermore, the sensitivity indices are calculated independently for each factor using factor-dependent model evaluations. Hence, when a factor X_k has converged, we can stop evaluating the model in the corresponding A_k^B matrices, consequently reducing computation time. In practice, a set of benchmarks can be defined in the base sample size $\{N_t\}_{t\in T}$ with $N_t < N$; when N_t iterations are reached, the factors that have converged from N_{t-1} to N_t, $\mathbb{F}_{conv}(N_t)$, are identified. From iteration $N_t + 1$, the model is no longer evaluated in A_k^B for X_k in $\mathbb{F}_{conv}(N_t)$. This strategy leads to a reduction in the analysis' computational cost of $\sum\limits_{t\in T} |\mathbb{F}_{conv}(N_t)| \cdot (N - N_t)$ model replications.

3.6 Discussion

We have defined a selection criterion for the Morris elementary effects method that allows to select the most important input factors using a criterion that mimics the *visual* selection. Ideally, the selection should be done visually. However, the *visual* selection is not easily applied consistently when the number of output variables is high and the discrimination among input factors is unclear. Furthermore, it cannot be applied in an automatic way, for example in bootstrap simulations. The new criterion defined here provides an approximation of the *visual* selection and has the advantages of being consistently applied in all the output variables and of being able to be used in an automatic way. Other authors use the *fixed number of factors* criterion applied to each output variable (DeJonge et al. 2012, Hussein et al. 2011, Morris et al. 2014). This approach is consistent along output variables, but could lead to unimportant input factors being selected in some cases and to important ones being discarded in others. Campolongo et al. (2007) use *Savage* scores (Savage 1956) to identify the most important input factors in a multidimensional output model. However, *Savage* scores are mostly used to compare ranking of input factors obtained using different approaches (Borgonovo et al. 2003, Confalonieri et al. 2010, Cucurachi et al. 2016) and their performance as a selection criterion has never been evaluated.

Campolongo et al. (2011) proposed an alternative way of sampling the input domain in the application of elementary effects screening method. This sampling scheme allows to use the model evaluations in the application of the Morris method in the application of the Sobol method, and it is not necessary to define levels for the input domain. In the examples tested, they found that the radial sampling proposed was superior in the computation of the elementary effects. We used the Morris method because it is still the most popular screening method used in the literature. However, the criteria proposed here could be used exactly in the same way changing the Morris sampling scheme by the radial sampling in the application of the elementary effects screening method.

The convergence could be assessed with the "factor screening" criterion in Sarrazin et al. (2016). This criterion focuses on the width of the confidence interval of the non-selected input factors (input factors X for which $m_X^r < 0.95 \cdot N_{boot}$) and considers that it has converged when the width is narrower than a certain threshold. However, as we are not interested in the value of the absolute elementary effect of the input factors, having narrow confidence intervals is not strictly necessary to ensure that they are in the lower part of the ranking. Hence, this criterion could led to a computational surcharge.

Most of the GSA methods focus on the variance of the output to describe its variability. However, variance is not able to represent the outputs' uncertainties correctly, for example, when model output is highly skewed (Borgonovo et al. 2011, Pianosi and Wagener 2015). This problem is solved with the use of "moment-independent" methods which do not use any specific moment to characterize uncertainty. The development of these methods has increased in the last years (Pianosi and Wagener 2015, Plischke et al. 2013). The two methods used in this chapter, the Morris and Sobol method, are based on the variance of the probability distributions. However, performance indicators of fisheries simulations models do not show, in general, a high skewness and we have wanted to focus on most common methods.

We propose the method by Lamboni et al. (2011) to calculate the generalized sensitivity indices. However, there exists other methods to deal with sensitivity measures for multidimensional output models. Gamboa et al. (2013) defined a new sensitivity index based on the decomposition of the output variables' covariance. In the framework of metamodels, Garcia-Cabrejo and Valocchi (2014) developed an analytical expression for multivariate sensitivity indices of polynomial chaos expansion. Recently, Xu et al. (2018) proposed an index to assess the inputs' effect on the entire joint probability distribution of the multivariate output. We chose Lamboni et al.'s (2011) method to calculate the multivariate indices because of its simplicity and ease of application. Gamboa et al. (2013) did not have any apparent advantage over Lamboni's method but its implementation was more complex. We discarded Garcia-Cabrejo and Valocchi's (2014) method, because it requires adjusting a metamodel based on the polynomial chaos expansion. The most recent method, Xu et al.'s (2018), uses an index to assess the inputs' effect on the entire joint probability distribution of the multivariate output but its application is complex.

Sheikholeslami et al. (2019) propose a method to automate the grouping of factors based on merging input factors with similar sensitivity indices. Conversely, we propose the grouping of factors based on their nature. The strategy of Sheikholeslami et al. (2019) is optimal in terms of convergence speed and stability but if input factors with very different nature were merged the interpretation of results could be difficult.

The explicit simulation of the MP differentiates MSE simulation models from other simulation approaches in fisheries management (Punt et al. 2016). The input factors corresponding with the observation of variables in the OM require an specific conditioning to overcome correlation between input factors as proposed in one of the guidelines. The explicit incorporation of the errors committed in the MP, as proposed in Section 3.5.3, allows to separate epistemic uncertainty from natural variability and could help in the definition of sampling programs and application of stock assessment models.

When the number of input factors is low, the save in computational cost derived from the application of the guideline related with the convergence of individual factors could be marginal. However, when the number of input factors is high the convergence rate among input factors could be very different. Hence, to stop evaluating A_k^B for input factors that have a quick convergence rate would lead to a great save in the computational cost of the analysis.

The computational cost of the variance decomposition method increases exponentially with the number of input factors. Furthermore, The greater the number of input factors, the greater the base sample size needed to sample the entire input domain correctly and achieve convergence, i.e., the method suffers the curse of dimensionality (Sheikholeslami et al. 2019). If we add that the execution time of fisheries simulation models is usually high, it becomes extremely important to reduce the dimension of the model, i.e to reduce the number of effective input factors to fight the curse of dimensionality. The aim of both, the proposed methodology to combine the Morris and Sobol methods, and the guidelines related with the conditioning of the model, is to reduce the number of effective input factors in the model. Furthermore, the guidelines can be used to overcome the correlation between input factors which is crucial to allow the application of standard GSA methods. Hence, the guidelines and criteria defined in this chapter are useful to promote the use of GSA methods by non-experts and reduce the computational cost of the analysis.

Chapter 4

Bio-economic multi-stock reference points as a tool for overcoming the drawbacks of the landing obligation

The work carried out in this chapter has been published in ***ICES journal of Marine Science*** *and presented in MYFISH symposium on* ***Targets and Limits for Long-term Fisheries Management*** *with the same title used in the chapter "Bio-economic multi-stock reference points as a tool for overcoming the drawbacks of the landing obligation":*

4.1 Introduction

Fisheries management in Europe comes under the CFP. The CFP is revised every few years, with the latest reform having been made in late 2013. The main innovations were the landing obligation of all catches and a governance shift towards regions (Salomon et al. 2014). The landing obligation policy was introduced gradually, for some fleets, the rule was implemented in January 2015 and for the rest it was implemented in 2019 (Salomon et al. 2014). Although MSY has been the management target in Europe for years, it was not until the last reform when it was introduced explicitly in the CFP.

The landing obligation is expected to have a big impact on the performance of the fishing fleets, especially in the so-called mixed fisheries where a variety of stocks are caught simultaneously and they cannot discriminate among the stocks they catch. These fleets will be obliged to stop fishing when the quota of any of the stocks they catch is reached. In order to reduce the impact of the landing obligation policy, the fleets could employ more selective gears or direct their effort to areas where the bycatch of unwanted stocks is lower. However, these measures are not always feasible or economically profitable. The major causes of discard in Europe are the minimum landing size, the TAC and quota limitations, and the low or null economic value of catches (Borges 2015).

TAC advice in Europe has traditionally been given on a single-stock basis without taking into consideration the interactions among stocks at fleet level. Inconsistencies between single-stock TAC advice in a mixed fisheries context is an important reason for over-quota discards (Ulrich et al. 2011). For this reason and in the wake of the closure of the cod fisheries in the North sea in 2002, European fisheries scientists started working on reconciling single-stock TACs in a mixed fisheries context (Vinther et al. 2004). Currently, the Fcube method (Iriondo et al. 2012, Ulrich et al. 2011) is routinely used to provide mixed fisheries advice in the North sea (ICES 2014a). Outside the framework of ICES, Da Rocha et al. (2012) have developed a bio-economic model for calculating reference points in a mixed fisheries context. Fcube and the bio-economic model of Da Rocha et al. (2012) can be used to produce consistent single-stock TACs, i.e., catch levels that in theory will be exhausted simultaneously for all stocks. While the Fcube method could be used to harmonize single-stock TACs produced independently at stock level, the fishing mortality targets obtained with the model of Da Rocha et al. (2012) could be used directly to produce consistent single-stock TACs.

Since its announcement in 2013, the landing obligation policy has provoked great expectations among local administrations, fishermen and scientists. During this time, several studies have been published dealing with discarding practices and the landing obligation policy. Batsleer et al. (2013), Condie et al. (2014; 2013) and Hatcher (2014) focused on incentives to fishermen to comply with the landing obligation in various European fleets. Using different economic approaches they all conclude that the landing obligation needs to be accompanied by strong controls and enforcement in order to reduce discards. Simons et al. (2015) used a bio-economic model to evaluate the performance of two alternative discard-prevention strategies in the North sea saithe fishery. They found that the negative effects of the landing obligation could be reduced by allowing a quota increase for the most restrictive stock at the expense of the quota for the least restrictive stock. For the Atlantic Iberian Waters Fernandes et al. (2015) characterized the discards of trawler fleets and Wise et al. (2015) analysed the long-term bio-economic effect of selectivity changes in Portuguese crustacean trawler fleets. The first found that the minimum landing size for hake and blue whiting high-grading are the major reasons for discarding in this fishery and Wise et al. (2015) concluded that improvements in selectivity have little effect on the revenue of the fleets, a positive effect on the biomass of some target species and reduced fish bycatch.

In this work we focused on the Spanish demersal fishery operating in Atlantic Iberian waters and the main stocks they catch. The results in Fernandes et al. (2015) suggest that the landing obligation will significantly impact the performance of trawler fleets in this area. Apart from trawlers the fishery also comprises gillnetters and vessels using hooks and lines. From 2019 onwards, the discard plan for demersal species (EU 2015) affects fisheries targeting hake, nephrops, plaice and sole, which include the Spanish demersal fleets. Fishermen and the fishing industry recognize that discards are an unacceptable waste of natural resources that must be addressed. However, they consider that there is a lack of definition in the implementation of the landing obligation and they fear that there will be a big discrepancy between intended incentives and operational ones (de Vos et al. 2016).

Simons et al. (2015) carried out a quantitative forecast of the effect of the landing obligation policy in European fleets using an integrated bio-economic model. Their work focused on certain fleets operating in the North sea, as well as the existing technical interaction between the saithe and cod stocks. However, the results obtained cannot be extrapolated to the Iberian demersal fishery system, where several stocks are caught simultaneously and fleets are segmented with different target and bycatch species.

Here, we used a bio-economic MSE approach (Punt et al. 2016) to analyse the impact of the landing obligation on the Iberian waters fishery system. Furthermore, we investigated whether the drawback of the landing obligation could be overcome using multi-stock reference points to produce TAC advice. We compared the bio-economic performance of the system in eight scenarios, which differed in the reference points used, the implementation, or not, of the landing obligation and the model used to describe fleet dynamics. The work has standalone relevance, but also provides a tool that can be used to evaluate regional management plans for Iberian waters. The model has been conditioned following a participatory modelling process (Voinov and Bousquet 2010) in the framework of the MyFish project (http://www.myfishproject.eu/). The stakeholders validated the tool qualitatively, gave us insight into the conditioning of the model and proposed management scenarios of their own that were later tested and presented to them.

Figure 4.1: Case study area. Figure taken from Garcia et al. (2017a).

The chapter is organized as follows: first, in the material and methods section we describe the case study, the data used and the conditioning of the OM and the MP in `FLBEIA`. Then, in the same section we list the scenarios used to investigate the impact of the landing obligation, the proposed reference points and the indicators used to summarize the results. Afterwards, the results are analysed using the indicators defined in material and methods section and are presented at stock and fleet level separately. Finally, the discussion verses about the performance of the proposed reference points, the sustainability of the stocks and different aspects of landing obligation and fleet dynamics.

4.2 Material and Methods

4.2.1 The case study

Iberian waters comprise the northwestern waters of the Iberian Peninsula, corresponding to the ICES divisions 8c and 9a (Figure 4.1). Portugal and Spain are the main countries operating in this area with France making a minor contribution to the catch of some stocks. The demersal fleet catch comprises a great number of stocks, most of which have not an analytical assessment.

In 2012 the fishery was made up of 2524 vessels grouped into seven fleet segments.

Although our focus was the economic performance of the Spanish demersal fleets, the Portuguese fleets were also included, because they account for the remainder of the catch of the majority of the stocks included in the simulation. The Spanish fishery comprises four fleet segments, gillnetters, demersal trawlers, vessels using hooks and lines, and purse seiners. In turn, the Portuguese fleet is composed of three segments, demersal trawlers, polyvalent artisanal fishing boats and purse seiners. Purse seiners are pelagic, but were included in the analysis because they account for the entire catch of southern horse mackerel (*Trachurus trachurus*) not caught by the demersal fleets.

Eight stocks were explicitly included in the model, hake (*Merluccius merluccius*), megrim (*Lepidorhombus whiffiagonis*), four spot megrim (*L. boscii*), white anglerfish (*Lophius piscatorius*), mackerel (*Scomber scombrus*), southern horse mackerel (*T. trachurus*), western horse mackerel (*T. trachurus*) and blue whiting (*Micromesistius poutassou*). All these stocks are assessed analytically by ICES. The first four are demersal stocks whose distribution coincides with the area of interest. The rest are pelagic stocks and only the distribution of southern horse mackerel coincides with the study area. Mackerel and blue whiting are widely distributed from Iberian waters to the northern Norwegian sea. In turn, horse mackerel in the northeastern Atlantic is divided into three stocks, the two considered in this study correspond with the southern stock distributed throughout Iberian waters and the western stock, which is found along the northeast continental shelf of Europe from the Bay of Biscay to Norway.

The contribution of the Iberian waters demersal fleets to the total catch of mackerel, blue whiting and western horse mackerel is around 3% for the first two stocks and about 16% for the third. Moreover, they only contribute significantly to the catch and income of trawlers. However, these stocks could play a crucial role under the new European landing obligation policy (Salomon et al. 2014) if the low quotas combined with a high abundance of stocks convert them into choke species (Schrope 2010) for the fleets. The eight stocks included account for 34%, 40% and 53% of the income of the gillnetters, longliners and trawlers, respectively (Table 4.1). The majority of the remaining stocks caught by the fleets are not assessed by ICES and for those which are, the data necessary to condition the simulation model is not available. Hence, in order to account for the income from the stocks not considered in the study, an artificial stock was introduced into the model (denoted as OTH).

All the stocks considered are subject to annual TAC and quotas. Technical measures such as limits mesh size restrictions, minimum landing sizes and spatio-

Table 4.1: Contribution of the stocks included in the model to the income of the Spanish demersal fleets. Reprinted from Garcia et al. (2017a).

Fleet	**Stock**	**Contribution to Income**
Gillnets	H.Mack (S)	1%
	Hake	25%
	Mackerel	5%
	Anglerfish	3%
	Total	34%
Longlines	Hake	26%
	Mackerel	13%
	Anglerfish	1%
	Total	40%
Trawlers	4S Megrim	5%
	B.Whiting	3%
	H.Mack (S)	1%
	H.Mack (W)	4%
	Hake	32%
	Mackerel	5%
	Megrim	1%
	Anglerfish	2%
	Total	53%

temporal closures are also in place.

In addition, a recovery plan for hake and Norway lobster (Council Regulation, CE 2166/2005) has been enforced in the area since 2006.

4.2.2 Data

Stock data used to condition the model was taken from the data used in ICES assessment working groups: hake, the two megrims and anglerfish from ICES (2013b); southern horse mackerel from ICES (2013a); blue whiting, western horse mackerel and mackerel from ICES ICES (2013a).

All the stocks, with the exception of hake and anglerfish, are assessed using annual age-structured models and the outputs of the assessments were directly used to condition the simulation model. Hake and anglerfish are assessed using quarterly-length-structured assessment models, Gadget (Begley 2004) and SS3 (Methot and Wetzel 2013), respectively. For hake, quarterly-length-based results were converted to annual age ones based on individual growth and mortality and for anglerfish the annual-age-based outputs of SS3 were used to condition the model.

Catch (landings and discards) and effort data by fleet and métier was compiled by national institutes, the IEO in Spain and the IPMA in Portugal, within the framework of the GEPETO project (Atlantic Area, 2011/1-159). Catch data included discard data for hake, megrims and mackerel and it was equal to landings for the other stocks. The landings and effort data were based on official statistics (logbooks, sales notes and fleet censuses) provided by the national administrations and discards were estimated using on-board sampling programs of IEO and IPMA. The data was desegregated by technical fleet groups as established by the European Data Collection Framework (DCF) (EC 2008). The fleet segment was defined as a group of vessels using the same predominant fishing gear throughout the year. In turn, métiers were identified by cluster analyses of catch profiles per trip (Castro et al. 2010, Punzón et al. 2010). The list of métiers by fleet is given in Table 4.2.

Table 4.2: List of métiers by fleet with the notation used along the text and figures and a short description. The métiers in vessels using hooks and lines and gillnetters are the same. Reprinted from Garcia et al. (2017a).

Fleet(s)	**Metier**	**Description**
Trawlers	OTB_DEF	Bottom otter trawl targeting hake, anglerfish and megrim using "Baka" nets.
	OTB_MPD	Bottom otter trawl targeting mixed pelagic and demersal fish using "Baka" nets.
	PTB_MPD	Bottom pair trawl targeting mixed pelagic and demersal fish.
Vessels using & Gillnetters	GTR_DEF	Trammel net targeting demersal fish with mesh size range 60-79
	LHM_DEF	Hand line targeting demersal fish
	LLS_DEF	Longline targeting demersal fish
	GNS_DEF_100	Set gillnet targeting demersal fish with mesh size $\geq$ 100
	GNS_DEF_60-79	Set gillnet targeting demersal fish with mesh size range 60-79
	GNS_DEF_80-99	Set gillnet targeting demersal fish with mesh size range 80-99

Monthly fish price data from 2001 to 2012 for all the stocks was obtained from a webpage of the regional government of Galicia (www.pescadegalicia.com). The data showed seasonal patterns and a weighted mean of the price over months, using the monthly catch as weight, was used to calculate the average annual price. The prices did not show any clear trend throughout the years and the average price for 2010 to 2012 was used to condition the model in the projection. Prices were only available at the regional level and the same price was used for all the fleets, métiers and age groups. As the catch composition of the stocks included in OTH varied by métier, the mean price of OTH stock was calculated at métier level. Catch and price data for the stocks included in OTH, at métier level, were only available for 2011; hence the mean price per ton at métier level in that year was used to condition the price of OTH stock in the projection. Fishing costs were obtained from the Annual Economic Report on the EU Fishing Fleet (STECF 2014). The costs in the report were given by gear and vessel length and a weighted mean, using effort as weighting factor, was used to calculate them by gear. Fixed costs were calculated per vessel and by definition were assigned at fleet level. Variable costs were calculated by unit of effort and were only available at fleet level; hence they were equal for all the métiers within the same fleet. Both costs were assumed to be constant throughout the simulation.

4.2.3 Conditioning

The models used to simulate the dynamic of the stocks and the fleets are summarized in Table 4.3 and described in more detail in the following sections.

4.2.3.1 Stocks

The five stocks distributed throughout Iberian waters were simulated using an age-structured exponential survival model together with a stock-recruitment model to generate the new cohorts. The recruitment of hake was modeled using the Bayesian Ricker model estimated in Cerviño et al. (2013). In each of the iterations of the model, a set of stock-recruitment parameters were randomly drawn from the joint posterior probability distribution. For the other stocks, a deterministic segmented regression model was adjusted to the historical recruitment and spawning stock biomass (SSB) data. Recruitment uncertainty in the projection was introduced using a multiplicative lognormal error around recruitment point estimates. The median of the error was equal to one and the coefficient of variation was equal to the historical one obtained in the model fit. Thus, hake's recruitment had two sources of uncertainty, one coming from the random Bayesian parameters and a second one arising from the uncertainty around the model curve.

In the projection, the abundance of widely-distributed stocks, blue whiting, west-

Table 4.3: Models used for each stock and fleet in each model component in Figure 2.1. Reprinted from Garcia et al. (2017a).

Component		Stock/Fleet	Models Used
Operating Model	Biological	Hake	Exponential Survival & Ricker Recruitment Model
		H.Mackerel 4 Spot M. Megrim Monkfish	Exponential Survival & Segment Regresion Recruitment Model
		Western H. Mac. Mackerel Blue Whiting	Age Structured Fixed Population
		OTH	No population
	Fleet	Spanish Trawlers Spanish Gillnetters Spanish Longliners	Multi-metier fleets. Effort share along metiers given as input data. Schaefer catch production model. Total effort calculated for the quota share of all the stocks and the one most similar to the previous one is selected. Entry-Exit model.
		Portuguese Trawlers Portuguese Polivalent Spanish Purse Seiners Portuguese Purse Seiners	Single Metier fleets. Total effort in each step restricted by the most relevant stock caught. No economics considered.
Management Procedure	Observation	Hake H.Mackerel 4 Spot M. Megrim Monkfish	All the variables are oberved with error. Two types of errors multiplicative and aging error. Stock numbers at age and fishing mortality at age not estimated through assesssment model, generated in the observation model.
		Rest of the stocks	Not observed
	Assess.	All the stocks	No assessment model
	Advice	Hake H.Mackerel 4 Spot M. Megrim Monkfish	The harvest control rule (HCR) used by ICES in the framework of MSY.
		Western H. Mac. Mackerel Blue Whiting	The historical TAC with uncertainty

ern horse mackerel and mackerel, was maintained constant and equal to the 2010-2012 mean level. The biomass of OTH stock was also constant and equal to one thousand billion (1e12) tons throughout the simulation. The biomass level was set sufficiently high to ensure that it would not restrict the catch of OTH stock in the projection.

The biological parameters, natural mortality-, weight- and maturity-at-age were considered constant and equal to the average of last three data years for all the stocks. In the case of widely distributed stocks, as population size was constant in the simulation, only weight-at-age was used.

4.2.3.2 Fleet dynamics

The catch was generated using a Cobb Douglas production function (Cobb and Douglas 1928) with constant return to scale (elasticity parameters equal to 1). Historical catchability (2010-2012) was calculated using historical biomass and effort data in the Cobb Douglas function, i.e., catchability was equal to the ratio between catch and the product of biomass and effort. In the projection, catchability was assumed to be constant and equal to the 2010-2012 average. Effort share between métiers was constant and equal to the average of the last three years in the traditional fleet dynamics approach and was a model variable in the profit maximization approach. Selectivity-at-age was implicitly included in catchability, assuming catchability is the product of selectivity, vulnerability and availability (Arreguín-Sánchez 1996). Hence, it was constant and equal to the average of the last three data years. In turn, the catch was divided into landings and discards using a retention ogive that was calculated as a ratio of landings- and catch-at-age data. In the projection, the average of last three years' retention ogives was used. The only fleets with discards were the trawlers, which discarded hake, megrims and mackerel.

The short-term dynamics of Spanish demersal fleets were simulated using two different approaches, one based on tradition and another on profit maximization. For the Portuguese fleets and Spanish purse Seine fleet only the traditional approach was used because no economic data was available.

The traditional fleet dynamics approach was based on the Fcube method (see Section 2.2.1.2 and Ulrich et al. (2011)). First, the total effort that corresponded with the catch quota of each of the stocks, $E_{st,y}$, was calculated. Then, assuming no landing obligation, the effort that was closest to that of the previous year was selected, mathematically:

$$E_y = E_{st_0,y} \quad \text{where} \quad \left|1 - \frac{E_{st_0,y}}{E_{y-1}}\right| = \min_{st}\left(\left|1 - \frac{E_{st,y}}{E_{y-1}}\right|\right)$$

where y and st are the subscripts for year and stock respectively and E_y is the total effort in year y. Under the landing obligation policy, as over-quota discards were not allowed, total effort was equal to the lowest effort, mathematically:

$$E_y = \min_{st}(E_{y,st})$$

In the profit maximization approach, the effort share between métiers and the total effort to maximize profits were calculated using the profit maximization approach described in Section 2.2.1.2 and equation (2.1). The optimization was restricted by the capacity of the fleet and the hake quota, assuming no landing obligation and by all the quotas subject to the landing obligation. It should be noted that with this model, the overall selection pattern of the fleet alters with the change of effort distribution between métiers.

The long-term dynamics of the fishery, i.e., the entry and exit of vessels in the fishery, were modeled using the model described in Section 2.2.1.2 (Salz et al. 2011). Here, the (dis)investment in vessels depends on the difference between revenue and the amount of revenue needed to cover both fixed and variable costs. If the difference is positive and the fleet is operating at full capacity, the number of vessels is increased. On the contrary, if the difference is negative the number of vessels is decreased. The annual variation was restricted to 3% because historically the decrease in capacity has always been below 3%. Furthermore, no more than 20% of the profits could be used to buy new vessels. The investment data from different Basque fleet segments (purse seiners, hookers and trawlers) was compared to their profits. There was enormous inter-annual variability in the resulting percentages and the average between segments (20%) was used to condition the model. The model was only applied to the Spanish demersal fleets, for the rest of the fleets the number of vessels was kept constant.

4.2.4 The Management procedure

Within the MP the focus of this study was in the performance of the HCR. Hence, it was assumed that the data (landings- and discards-at-age) and the stock status were known without error. The difference between the real system in the OM and the data used to generate management advice in the MP arose from the two year time lag between the data used to calculate and to implement the TAC. The same happens in reality where the TAC for year y, is calculated the year before, $y-1$, using data and stock estimates up to previous year, $y-2$. Hence, when the fleets caught the TAC in year y, the stocks in the real system could be different from the estimated stocks used to calculate the TAC.

From 2013 to 2015 historical TACs were utilized instead of using a HCR to produce them. From 2016 onwards, the ICES MSY framework HCR (ICES 2012) was used to generate annual TAC advice. The objective of this HCR is to maintain stock exploitation at levels in accordance with MSY. The HCR uses three reference points, a fishing mortality target, F_{msy}, and two SSB reference points, B_{trigger} and B_{lim}. When the SSB of the stock is above B_{trigger} the TAC advice corresponds with F_{msy} and when it is between B_{trigger} and B_{lim} the fishing mortality is decreased linearly. Below B_{lim} ICES has not defined a universal rule and in this study we used zero TAC advice. The fishing mortality was translated into TAC using the Baranov catch equation (Baranov 1925). Biomass reference points were not available either for the demersal stocks or the southern horse mackerel. For these stocks the biomass references points were computed using a common ICES approach where B_{lim} is set as the lowest biomass observed in the historical time series and B_{trigger} is equal to $B_{\text{lim}} \cdot 1.4$ (Hauge et al. 2007).

Single-stock fishing mortality targets (F_{msy}) for demersal stocks and southern horse mackerel were taken from ICES assessment reports (ICES 2013a;b). Multi-stock fishing mortality reference points were calculated using the bio-economic optimization model developed by Da Rocha et al. (2012). The reference points corresponded with those that maximize the Net Present Value (NPV) of the whole fishery using a discount factor of 5%. The model returns a multiplier that applied to the *status quo* reference fishing mortalities of the stocks result in a fishing mortality that could produce the highest NPV in the long-term while maintaining biomasses above given reference points. The discount factor was selected based on macroeconomic literature (Prescott 1998) which considers 5% an adequate value for calibration. The *status quo* reference fishing mortality for each stock was calculated as the average over the last three data years (2010-2012) and the reference age range. The reference age ranges were taken from assessment reports (ICES 2013a;b). For widely-distributed stocks, instead of a HCR, a constant catch quota equal to the mean catch of last three years was used.

The landing obligation was implemented in 2018. Although the fishing mortality targets in the HCR were the same prior and subsequent to that year, up to 2017 the TAC was given in terms of landings and after 2017 in terms of catch. To calculate the TAC in terms of landings the retention ogive resulting from dividing landings-by catch-at-age was used.

4.2.5 Scenarios

Eight scenarios were run which depended on:

- The fishing mortality target used in the HCR: single-stock reference points used by ICES (denoted as ‘ices’), or multi-stock reference points calculated using the bio-economic model (denoted as ‘msmsy’).
- Fleet dynamics model using either a traditional approach (denoted as ’trad’) or profit maximization approach (denoted as ‘mpro’).
- Implementation, or not, of the landing obligation (denoted as ’lo’).

The eight scenarios resulted from a combination of the two options in each of the three points above. As the objective of the study was to evaluate whether multi-stock reference points overcome the drawbacks of the landing obligation, we had to compare the current management scenario, i.e., ICES reference points and no landing obligation, with the scenarios including the landing obligation and both sets of reference points. Additionally, we combined these scenarios with two contrasting hypotheses on fleet dynamics because there was a high uncertainty related to their real dynamics and this could have a great impact on the results. Table 4.4 lists the notation used for each scenario with the options used. Each scenario was projected from 2013 to 2025 using 250 independent iterations run in parallel.

Table 4.4: List of scenarios with the modelling options used in each of them. Reprinted from Garcia et al. (2017a).

Scenario	Reference Points	Fleet Dynamics	Landing Obligation
ices_trad	ices	traditional	No
ices_mpro		profit maximization	
msmsy_trad	msmsy	traditional	
msmsy_mpro		profit maximization	
ices_trad_lo	ices	traditional	Yes
ices_mpro_lo		profit maximization	
msmsy_trad_lo	msmsy	traditional	
msmsy_mpro_lo		profit maximization	

4.2.6 Indicators

The performance of the system was analysed using a set of indicators, at stock, fleet and fishery level in order to analyse the biological sustainability and economic performance of the system:

- $p(SSB < B_{\text{lim}})$ and $p(SSB < B_{\text{trigger}})$: for each stock and year the probability of being below B_{lim} and B_{trigger} respectively, calculated as the ratio between the number of iterations where SSB was below the reference biomass and the total number of iterations. This indicator measures the sustainability of the management strategies in biological terms.
- Quota uptake: for each stock, fleet and year, the ratio between the catch and the quota advice minus one. It shows the use of quotas at fleet level. With no landing obligation a value above 0 indicates the existence of discards. Under the landing obligation it is always equal or less than zero. The stocks

with quota uptake equal to zero are the stocks that limit the fleet's activity, which in cases where the quota is very small may act as choke species, severely constraining the possibility of the fleet to catch its fishing opportunities. Stocks with values close to -1 indicate wastage of fishing opportunities.

- Profits: the profits for each fleet and year, calculated as the revenue minus total costs. Total costs were calculated as the sum of fixed costs and variable costs. In turn, fixed costs were equal to $N_{\mathrm{V}} \cdot FxC$ and variable costs to $E \cdot VaC$. This indicator measures the annual economic performance of the fleets.
- Effort share: the proportion of effort exerted by each fleet in each métier and year. In the traditional approach scenario this indicator is constant by definition. In the profit maximization scenario it corresponds with the métier combination resulting in the highest profits under the given restrictions.
- NPV: the net present value of the Spanish fleet in the projection period using a discount factor of 5%, mathematically:

$$NPV = \sum_{y=2016}^{2025} \frac{PRF_y}{1.05^{1-2015}}$$

where PRF_y denotes profits in year y. This indicator measures the profitability of the whole Spanish fishery over the entire projection period taking into account the fact that one euro today is more valuable than one euro will be in fifteen years' time.

4.3 Results

The results were analysed at stock level for the stocks distributed exclusively in Iberian waters and at fleet level for Spanish demersal fleets.

4.3.1 Stock level

Reference points

Multi-stock and ICES fishing mortality targets and biomass reference points per stock are shown in Table 4.5. Multi-stock reference points implied a 30% reduction in *status quo* fishing mortalities. The multi-stock reference points were lower than the ICES single stock estimates except for hake, which showed an approximately 80% higher estimate.

The biomass reference points were well below the SSB in the most recent historical years for all the stocks except horse mackerel. The SSB in the initial year of the simulation was well above B_{lim} for all the stocks except horse mackerel, where the SSB was only 4% higher.

Table 4.5: ICES and multi-stock fishing mortality targets and biomass reference points, in thousands of tons, for the stocks distributed along Iberian waters exclusively. Reprinted from Garcia et al. (2017a).

	Hake	**H.Mackerel**	**Megrim**	**Four Spot Megrim**	**Anglerfish**
Ftarget - ICES	0.24	0.11	0.17	0.18	0.19
Ftarget - MSMSY	0.43	0.07	0.11	0.16	0.11
Blim	8836	215571	605	3205	1925
Btrigger	12371	301799	846	4487	2695

Spawning stock biomass

The probability of SSB being below B_{lim} was positive only for southern horse mackerel in the last two years of the two 'ices' scenarios with no landing obligation (Table 4.6). However, the probability was low ($\leq$ 3%). The probability of being below B_{trigger} was higher than 0, in at least one year, for southern horse mackerel in all the scenarios, as well as for the megrims in the 'msmsy-mpro' scenario (Table 4.6). The probability for the megrims was always less than 4%. For southern horse mackerel, the probability of being below B_{trigger} in the scenarios with no landing obligation and 'ices' reference points was greater than 20% for all the years from 2019 onwards. On the other hand, the probability in the scenarios with the landing obligation and 'msmsy' reference points was always less than 3%. In the 'ices-mpro-lo' scenario the probability from 2018 to 2021 decreased from 18% to 11%. In the other cases the probability was always less than 10%.

Fishing Mortality

In the scenarios with the landing obligation, fishing mortality decreased significantly when it was introduced in 2018. Beginning in that year, the fishing mortality time series became fairly stable throughout the projection in all the scenarios. In 2025, under the landing obligation, fishing mortality for all the stocks was well below the target (Figure 4.2). Under the current management framework and 'ices' reference points, fishing mortality was above the target only for hake (Figure 4.2). In contrast, using 'msmsy' reference points the fishing mortality of hake was the only one below the target. For the other stocks the fishing mortality was around the target, with the exception of anglerfish and four spot megrim in the profit maximization scenario, where the target was exceeded. In general, the uncertainty was low

Table 4.6: Probability of SSB being below B_{lim} and B_{trigger} from 2013 to 2025. Only the stocks and scenarios for which the probability is positive for any of the years is shown. Dark grey indicates probabilities above 15%, grey indicates probabilities between 6% and 15% and light grey indicates probabilities between 1% and 5%. Reprinted from Garcia et al. (2017a).

Scenario	**Stock**	**Prob. SSB below**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**	**2025**
ices-trad	Southern H. Mackerel	B_{trigger}	100	0	0	0	0	10	**26**	**36**	**42**	**38**	**35**	**50**	**62**
msmsy_trad			100	0	0	0	0	2	7	12	12	6	3	6	11
ices-trad_lo			100	0	0	0	0	10	9	9	6	3	1	1	2
msmsy_tradlo			100	0	0	0	0	2	1	2	1	0	0	0	0
ices_mpro			100	0	0	0	2	**18**	**35**	**44**	**51**	**52**	**48**	**65**	**74**
msmsy-mpro			100	0	0	0	0	0	3	6	6	4	1	4	6
ices-mpro_lo			100	0	0	0	2	18	18	15	11	4	1	2	2
msmsy-mpro_lo			100	0	0	0	0	0	1	1	0	0	0	0	0
msmsy-mpro	4S Megrim	B_{trigger}	0	0	0	0	0	0	2	2	2	2	2	2	3
msmsy-mpro	Megrim		0	0	0	0	0	0	1	0	0	0	0	0	0
ices-trad	Southern H.	B_{lim}	0	0	0	0	0	0	0	0	0	0	0	0	1
ices-mpro	Mackerel		0	0	0	0	0	0	0	0	0	0	0	1	2

and under the landing obligation it was even lower. The scenarios with the highest uncertainty corresponded to profit maximization scenarios.

4.3.2 Fleet level

Profits

The profits were highly affected by the fleet dynamics model. In the short-term there was an adjustment period with high inter-annual variability, but in the long-term the time series were fairly stable. Under both fleet dynamics models the effect of the landing obligation and reference points was fleet dependent.

In the traditional fleet dynamics scenario, vessels using hooks and lines obtained higher profits when the landing obligation policy was in place, both in the short- and long-term (Figure 4.3). Furthermore, the increase in profits was enhanced by the use of 'msmsy' reference points. On the contrary, the profits of trawlers were lower, although the difference was somewhat reduced in the long-term (Figure 4.3). In the short-term, the profits obtained in the 'msmsy-trad-lo' scenario were almost the same as those obtained in the 'ices-trad' scenario. However, in the long-term the profits in 'msmsy-trad-lo' scenario were significantly lower. The landing obligation caused a decrease in the profits of gillnetters in the first years of implementation and an increase in the final year of simulation (Figure 4.3). As with trawlers, the use of 'msmsy' reference points cushioned the impact of the landing obligation in the short-term, but it generated a loss in profits in the long-term.

In the profit maximization dynamics scenario the landing obligation produced a decrease in the profits of vessels using hooks and lines and trawlers in the short-term (Figure 4.3). For gillnetters the profits were slightly higher. Under the landing obligation 'msmsy' reference points resulted in higher profits than 'ices' reference points for all the fleets. However, in the short-term they did not cover the losses observed in trawlers and vessels using hooks and lines. In the long-term, profits were covered for the vessels using hooks and lines, but not for trawlers. In general, the loss in profits derived from the landing obligation under profit maximization dynamics was lower than that observed for traditional fleet dynamics.

Quota share utilization

By definition, under the landing obligation policy the quota was not exceeded for any of the stocks. In the traditional fleet dynamics scenario, quota uptakes in 2025 were low in general and even lower under the landing obligation (Figure 4.4). The effect of 'msmsy' reference points was slight and stock dependent. For

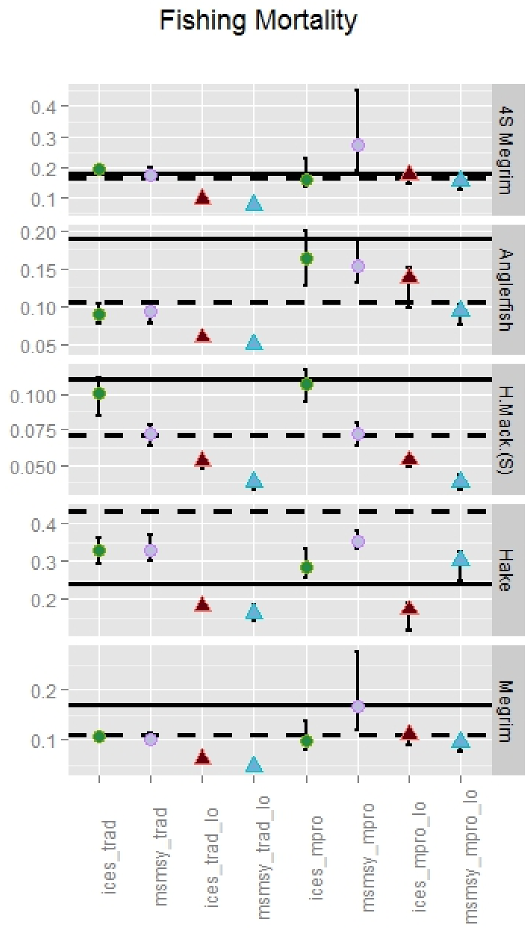

Figure 4.2: Fishing mortality in 2025. The points indicate the median value and the vertical lines correspond with the 95% confidence intervals. Circles correspond with scenarios without landing obligation and triangles with scenarios with landing obligation. Red points correspond with 'ices' reference points and traditional fleet dynamics, green with 'msmsy' reference points and traditional fleet dynamics, blue with 'ices' reference points and profit maximization fleet dynamics and purple with 'msmsy' reference points and profit maximization fleet dynamics. Horizontal lines correspond with fishing mortality targets, solid one correspond with 'ices' reference points and dashed one with 'msmsy' ones. '4S Megrim' stands for 'four spot megrim' and 'H.Mack (S)" for 'southern horse mackerel'. Figure taken from Garcia et al. (2017a).

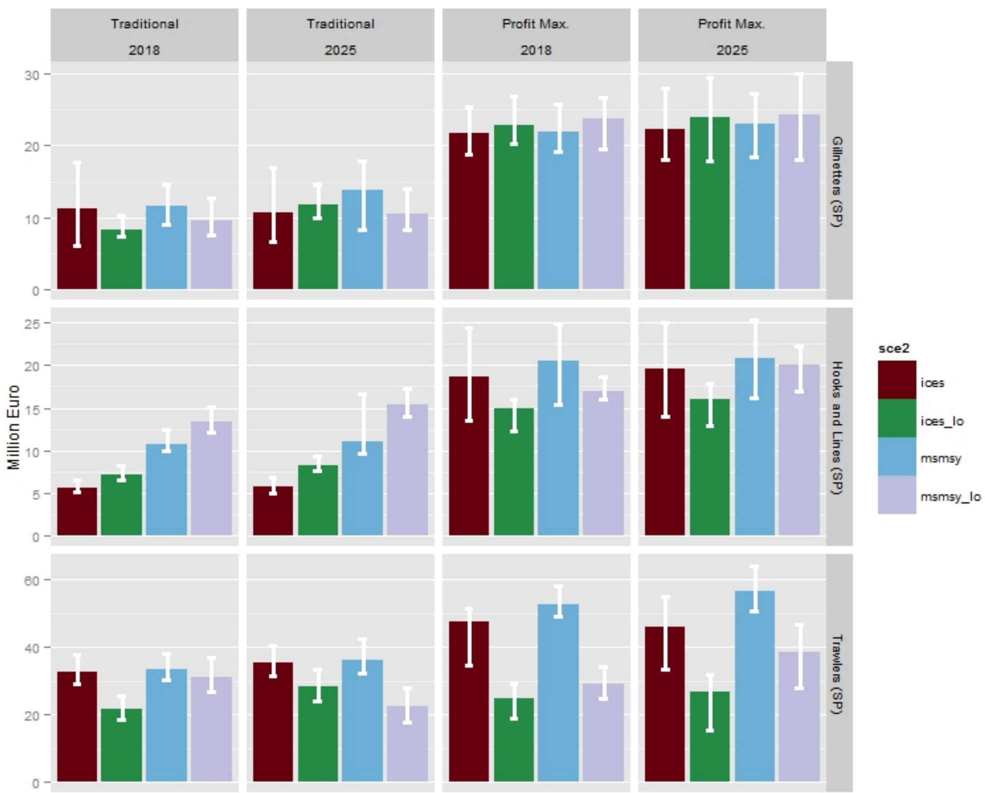

Figure 4.3: Spanish demersal fleets' profits in 2018 and 2025 by fleet dynamics model scenario. Bars correspond with median values along iterations and vertical lines with 95% confidence intervals. Figure taken from Garcia et al. (2017a).

gillnetters and trawlers the utilization under the landing obligation was lower than under the current management framework and for vessels using hooks and lines it was higher (Figure 4.4). Southern horse mackerel and hake were the limiting stocks for gillnetters (Figure 4.4). Furthermore, the former was a choke stock which produced a decrease of 23% in profits (Figure 4.3). In the scenarios with no landing obligation and when these stocks were not limiting the effort, their quota was exceeded. The quota uptake of anglerfish was significantly higher in the scenarios with 'msmsy' reference points. The quota uptake of mackerel and OTH catch was slightly affected by the landing obligation. Hake was always the limiting stock for vessels using hooks and lines and the quota was not exceeded for any of the stocks (Figure 4.4). The quota uptake of non-hake stocks was more than 20% higher when 'msmsy' reference points were used. The effort of trawlers was restricted by the western horse mackerel quota when there was no landing obligation. With the landing obligation southern horse mackerel and hake became the choke stocks in the 'ices' and 'msmsy' reference point scenarios causing a loss of 20% and 36% in profits, respectively (Figures 4.3 and 4.4).

Using profit maximization fleet dynamics, the quota uptake and over-quota in 2025 was significantly higher than under traditional fleet dynamics (Figure 4.4). The gillnetters' quota of southern horse mackerel was highly underutilized in all the scenarios except in the 'mpro-msmsy' scenario (Figure 4.4). In contrast, the quotas of hake, mackerel and anglerfish were almost fully consumed in all the scenarios. The catch of OTH stock was always above the historical catch particularly in 'msmsy' scenarios. Vessels using hooks and lines fully consumed their quota of hake and mackerel in all the scenarios (Figure 4.4). The over-quota of some stocks in vessels using hooks and lines and trawlers was very high and it was even higher when 'msmsy' reference points were used (Figure 4.4). The catch of OTH stock was higher than historical catch only when the landing obligation was not in place (Figure 4.4). The quota of blue whiting was highly underutilized in all the scenarios. For trawlers, the quota utilization under the landing obligation was significantly higher when 'msmsy' reference points were used.

Effort share

In vessels using hooks and lines, almost all the effort concentrated in a métier that was minor in the past (GTR-DEF); on the other hand the effort in the principal métier (LLS-DEF) was low in general (Figure 4.5). The effort distribution of gillnetters was concentrated in the métier with the highest effort in the historical period, except in the 'msmsy-mpro-lo' scenario (Figure 4.5). In this scenario the

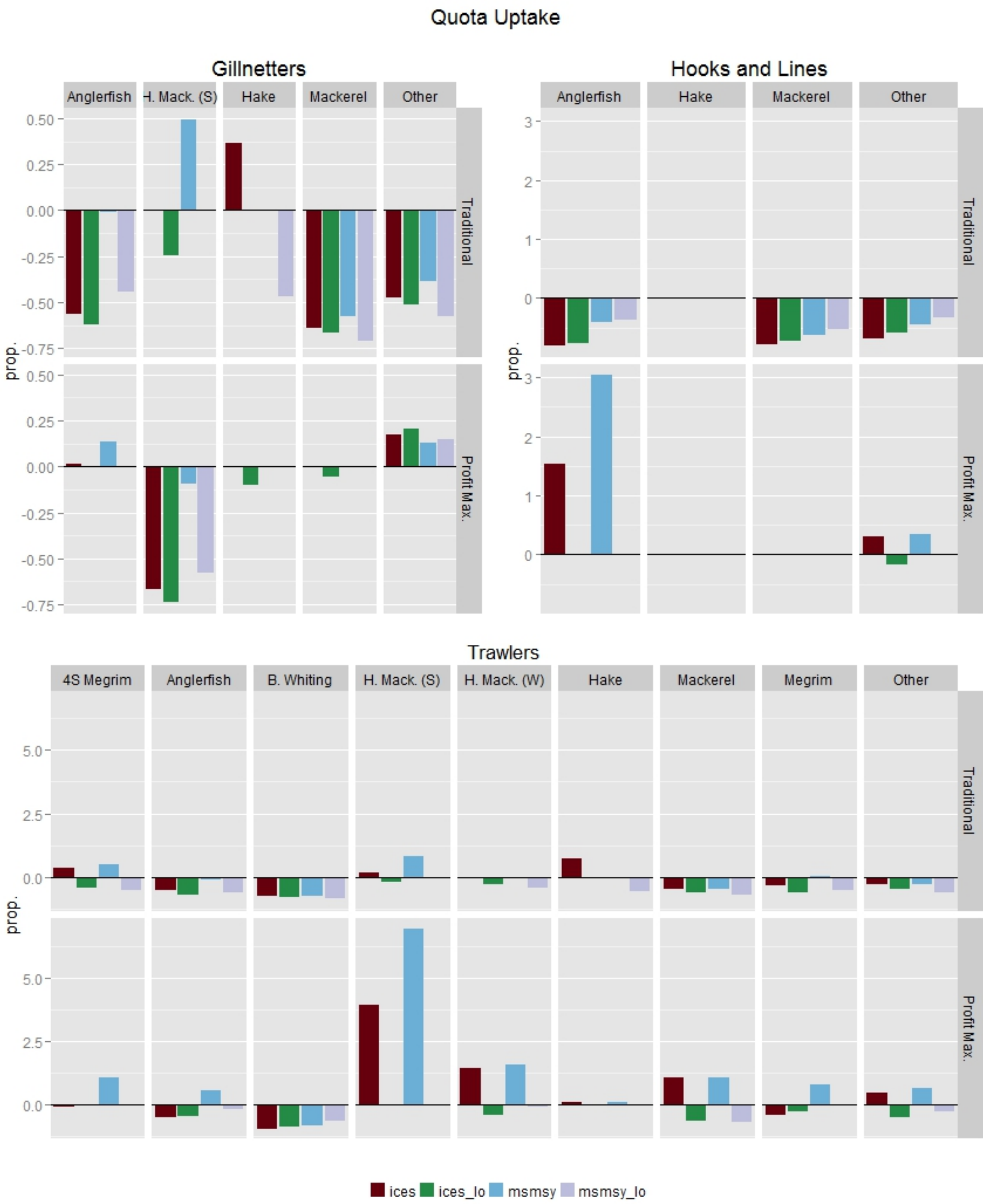

Figure 4.4: Spanish demersal fleets' quota uptake in 2025 by fleet dynamics model scenario. Bars correspond with median values. For other stock the bar corresponds with the ratio between catch in 2025 and historical catch instead of quota uptake ('4S Megrim' corresponds with 'four spot megrim', 'B. Whiting' with 'blue whiting', 'H. Mack (S)' with 'southern horse mackerel' and 'H. Mack (W)' with 'western horse mackerel'). Figure taken from Garcia et al. (2017a).

uncertainty was very high and although in median 75% of the effort concentrated in one métier (LLS-DEF) the 90% probability interval covered almost the whole domain. The effort share per scenario in trawlers was more variable than in the rest of the fleets (Figure 4.5). With no landing obligation, the effort concentrated in the OTB-MPD métier, especially in the case of 'ices' reference points where, in median, all the effort was exerted in this métier. Under the landing obligation, the effort distribution was more heterogeneous and closer to the historical effort distribution. With the exception of the 'msmsy-mpro-lo' scenario for gillnetters, the uncertainty was low.

Net present value

The 'msmsy' reference points were designed to maximize NPV, as such these scenarios performed better with relation to NPV than the homologous 'ices' scenario. The highest NPV was obtained when no landing obligation was combined with 'msmsy' reference points and the lowest was obtained under the landing obligation and 'ices' stock reference points, independently of the fleet dynamics model used (Table 4.7). The loss in profits under the landing obligation was reduced when 'msmsy' reference points were used. The NPV under traditional fleet dynamics, landing obligation and 'msmsy' reference points (msmsy-trad-lo scenario), was slightly higher than the NPV under current management framework ('ices-trad' scenario), (Table 4.7). Using profit maximization dynamics, the NPV in 'msmsy-mpro-lo' scenario was lower than under the current management framework ('ices-mpro' scenario), but was significantly higher (12%) than using single-stock reference points with the landing obligation (ices-mpro-lo scenario) (Table 4.7).

Table 4.7: Net present value of demersal Spanish fleets in each scenario. Current management refers to 'ices-trad' and 'ices-mpro' scenarios (i.e., ices reference points and no landing obligation). Reprinted from Garcia et al. (2017a).

Fleet Dynamics	**Scenario**	**Euros**	**Difference with current management**
Traditional	ices_trad	556	-
	msmsy_trad	597	107%
	ices_trad_lo	517	93%
	msmsy_trad_lo	558	100%
Profit Maximization	ices_mpro	888	-
	msmsy_mpro	969	109%
	ices_mpro_lo	778	88%
	msmsy_mpro_lo	870	98%

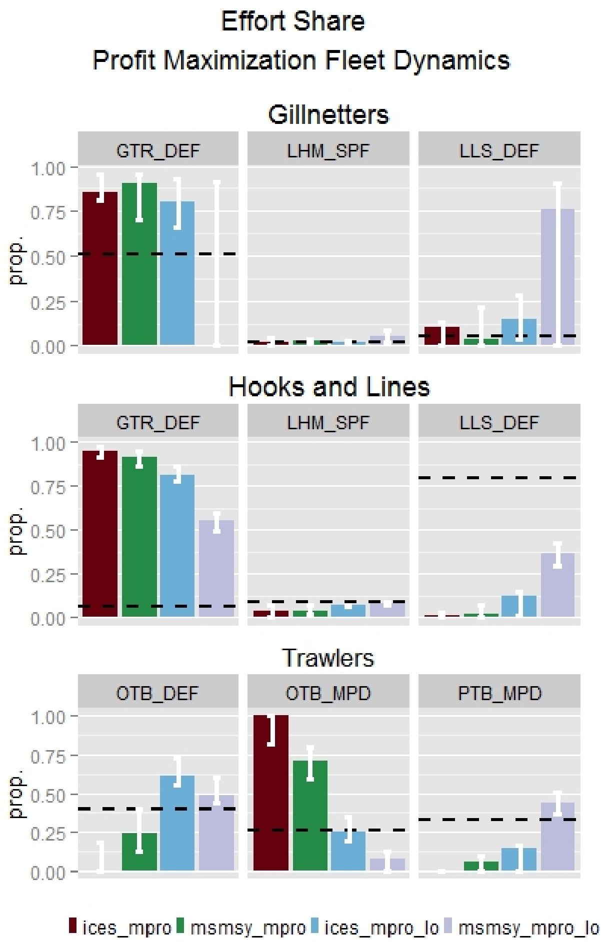

Figure 4.5: Spanish demersal fleets' effort share in 2025 in profit maximization fleet dynamics scenarios for the most important metiers. Bars correspond with median values, vertical lines with 95% confidence intervals and dashed horizontal lines with the average historical effort share in each of the métiers. Figure taken from Garcia et al. (2017a).

4.4 Discussion

In this study we analysed the bio-economic performance of the Iberian waters demersal fishery system under different management scenarios. The management scenarios are distinguished by the reference points used and the implementation, or not, of the landing obligation policy. Moreover, two different fleet dynamics models were used to describe the fleet behaviour, one based on tradition and another one on profit maximization. Various indicators at stock, fleet and fishery level were analysed to evaluate the sustainability of the management strategies and investigate whether the loss in the profits of the fleets caused by the landing obligation can be overcome using multi-stock reference points.

Performance of multi-stock reference points

This is the first time that multi-stock reference points, as proposed by Da Rocha et al. (2012), have been tested at fleet level. Their implementation in practice has been proven to partially overcome the loss in profits under the landing obligation. At the fishery level, ‘msmsy’ reference points compensated the losses derived from the landing obligation using current ‘ices’ reference points, independently of the fleet dynamics employed. The lower profits seen in ‘msmsy-mpro-lo’ and ‘msmsy-trad-lo’ scenarios compared to those in ‘ices-mpro’ and ‘ices-trad’ scenarios in some fleets were compensated for by higher profits in other fleets. At fleet level, this depended on the fleet itself and the time period. Under profit maximization, ‘msmsy’ reference points always compensated, to some extent, the losses of the landing obligation, independent of the time period and fleet. Under traditional fleet dynamics, ‘msmsy’ reference points compensated for the losses in all the fleets in the short-term, although in the long-term, under the landing obligation, the profits of trawlers and gillnetters were lower in ‘msmsy-lo’ scenarios.

Multi-stock reference points were estimated by multiplying the *status quo* fishing mortalities by a common factor. Therefore as *status quo* fishing mortalities were, in percentage, at the same distance from the targets, a simultaneous depletion of the catch quotas of these stocks was expected. However, this did not occur in any of the ‘msmsy’ scenarios. There were three differences between the real system and the system estiamted in the MP which precluded the simultaneous exhausting of quotas. Firstly, in the real system the catch was calculated using the Cobb-Douglas function (Cobb and Douglas 1928) and in the MP the TAC was calculated using Baranov catch equation (Baranov 1925) (see Section 2.2.1.2 for details on the difference between both equations). Secondly, as the TAC is calculated the year before its implementation using data up to two years before, there was a two-year time lag between the calculation of the TAC in the MP and its implementation in the OM. Finally and most importantly, the inter-species catch profiles at fleet level differed from that used at overall level to calculate the TAC advice. Hence, the quota consumption at fleet level was not reached simultaneously.

Stock sustainability

Both sets of reference points, single- and multi-stock, were precautionary in the sense defined by ICES (ICES 2014c), i.e., the probability of being below B_{lim} was less than 5% for all the stocks and scenarios. In the case of hake, where the multi-stock reference point was almost double than the ICES reference point, the biological risk for the stock was not increased. This was not surprising given that the hake multi-stock reference point is between Beverton-Holt (0.23) and Ricker (0.56) MSY fishing mortalities estimated by Cerviño et al. (2013) and the stock-recruitment model used to simulate recruitment was the Ricker model proposed in that study. This suggests that current hake fishing mortality target could be increased without increasing the risk for the stock. However, in order to propose this as a new management target, at least its robustness to different stock-recruitment dynamics should be evaluated.

Impact of the landing obligation at fleet level

The impact of the landing obligation depended on the fleet, the fleet dynamics used and the time period (short- or long-term). The landing obligation rewarded the most selective fleets, namely vessels using hooks and lines and gillnetters, as observed in Condie et al. (2014). The catch quota utilization of these fleets was higher and therefore so were their benefits. Moreover, these fleets do not have undersize discarding like trawlers. Hence, the quota uplift derived from generating the TAC in terms of catch instead of landings, since the implementation of the landing obligation, fully contributed to their landings. However, the trawlers had to use this increment to cover the undersize discards that counted towards the quota and did not produce any revenue. Here, the quota uplift was divided among fleets in the same percentages as the TAC quotas. In reality, it is be distributed per country using relative stability and, afterwards, member states can use it to compensate the fleets most affected by the landing obligation. This could benefit the corresponding fleets but would reduce the CFP objective of improving selectivity by reducing catches of small individuals.

The catch quota uptake by vessels using hooks and lines and gillnetters depended on fleet dynamics. Under traditional dynamics, quota utilization was higher for hookers and lower for gillnetters, while this was reversed in a profit maximization scenario (Figure 4.3 and Figure 4.4). When the landing obligation was implemented, that resulted in an increase in the profits of vessels using hooks and lines under traditional fleet dynamics and those of gillnetters under profit maximization dynamics. In trawlers, the quota utilization was always lower under the landing obligation and thus the profits were always lower regardless of the fleet dynamics employed.

Jardim et al. (2010) analysed the recovery plan of southern hake using alternative fishing mortality targets combined with different discard scenarios. They concluded that Fmax = 0.25 combined with a total discard ban would be the best strategy in terms of sustainability and total yield. Furthermore, they suggested that the fishery would be more profitable under a discard ban scenario, in contrast to the results obtained in this study. They analysed the problem from a single-stock and single-fleet point of view and linked the discard ban to a hypothetical change in selection pattern leading to a very different conclusion about the effect at fishery level. This difference highlights the importance of using multi-fleet approaches and including all the stocks caught by the fleets when analyzing the economic performance of any management strategy. This is especially relevant in the case of selectivity scenarios where the benefits forecasted from a single-stock perspective could not compensate for the losses derived from the decrease in the catch of other stocks.

The importance of selectivity under the landing obligation

The métier definition uses data from the European data collection framework that groups trip data with common gear, vessel size, target ecological group and mesh size. This level of aggregation may underestimate the ability of vessels to discriminate between species. On the one hand, this is because ecological groups do not distinguish the stocks within a group and on the other, because the trip category may not be fine enough to capture the selectivity of the fleet. Trawlers, characterized for being unselective, make several hauls in the same trip. The catch composition of the hauls varies depending on the target species and in the same trip the skipper may change the target species from haul to haul. Moreover, under the landing obligation it is expected that skippers will try to be more selective in order to be able to consume all their quotas without exceeding any of them (Batsleer et al. 2013, Condie et al. 2013). In this sense, the traditional approach could underestimate the inter-species selectivity of the fleets and in reality quota-share utilization could be higher than estimated. Under a profit maximization scenario, the movement between métiers improves the quota-utilization in relation to the traditional approach; nevertheless, it could also underestimate the real utilization capacity. In some mixed fisheries, in order to understand the real inter-species selectivity of vessels, especially in mixed fisheries, units of measurement finer than "trip" and ecological group are necessary to define the métiers.

When subjected to the landing obligation, if selective fishing is not possible, the quotas of limiting stocks become an input management factor, i.e, they determine the amount of effort that the fleets are able to execute. In this regard, the loss in profits generated by the implementation of the landing obligation in some fleets is not only generated by the loss in the landing of the stocks subject to the quota system but from the loss in the landing of other valuable stocks for which there is no catch restriction. In fact, in the case of demersal fleets in Iberian waters the chance to catch OTH stock marked to a large degree the economic performance of the fleets. Although pelagic stocks are not the target stocks of the fleets considered in this study, under the landing obligation their quota in some cases became an input management measure that allowed fishing for the target stocks.

Implementation of the landing obligation in practice

In practice, the implementation of the landing obligation will be more complex than simulated here. On the one hand, the fleets will try to improve their selectivity to make the best use of fishing opportunities by changing their gear configuration (Bayse et al. 2016) and/or altering their behaviour (Batsleer et al. 2016). On the other hand, the landing obligation policy includes several exemptions (Salomon et al. 2014) that provide flexibility and which have not been simulated in this study. In turn, the change in selectivity will generate a change in Fmsy and the reference points will have to be recalculated in order to manage the fishery optimally. Therefore, the version of the landing obligation implemented here is the most restrictive possible and the impact on the fleets could be less than that forecasted.

Fleet dynamics models

Fleet dynamics models are a key element in the simulation of fishery systems (Fulton et al. 2011a). In this study, instead of looking for the model that best describes the dynamic of the fishery we have used the scenario approach ("what if"). Fishermen may not behave exactly as in the past and may not be able to execute the exact effort distribution that maximizes their profits but we expect that the real dynamic is somewhere in between. Other approaches to approximate fleet dynamics exist and have been applied elsewhere, for example Andersen et al. (2010) used a discrete choice model to predict effort allocation and Marchal et al. (2013) combined tradition with anticipated economic opportunities in the same model. A review of fishermen's tactical behaviour can be found in van Putten et al. (2012). They concluded that although economic drivers are the key components of fleet dynamics models, 'hybrid' models that include explanatory variables related to tradition are required to improve their predictability. In the case of `FLBEIA` this would imply, for example, combining the tradition and profit maximization models into a single, inclusive model. The pivotal question would be how to weight both approaches in practical implementations. Nøstbakken et al. (2011) carried out a literature review on economic models of strategic behaviour. They found that although there is a large amount of literature on the measurement of capacity, there is little work on investment modelling and most of it is theoretical. They encourage the incorporation of this type of models into bio-economic models in order to improve the medium- and long-term predictability of a fishery's response to management strategies.

Limitation of profit maximization dynamics

The profit maximization approach provides information on the gains that could be obtained from the fishery changing only the effort allocation. `FLBEIA` allows full flexibility to move from métier to métier as in FcubeEcon (Hoff et al. 2010). In practice, this flexibility resulted in an effort distribution far from the historical distribution, so much so that in some cases the historically more important métiers almost disappeared. Under the landing obligation a big change was expected as the fishermen reacted to the new situation. However, in the case of vessels using hooks and lines and trawlers, the change was greater under the current management framework. The effort share in these fleets under no landing obligation was concentrated mainly in one métier which did not match the historically more important métier. Under the landing obligation the flexibility of the model was restricted by the discard ban. Hence, the fleets were forced to diversify their effort among métiers in order to make the best use of their quotas without exceeding any of them. Uncertainty in the gillnetters' effort share was very high in the 'msmsy-mpro-lo' scenario. However, the uncertainty was not translated into profits, meaning that the optimization surface was quite flat and different combinations of effort share produced similar profits.

In practice, the mobility between métiers could be restricted by different factors. In the case of trawlers, the seasonality of the OTB-MPD métier restricts the amount of effort that the vessels can expend in it, as pelagic stocks only approach the Iberian coast in the spring months. As in this case `FLBEIA` implementation is annual, an additional restriction in the profit maximization function would be needed to limit the effort in this métier. In the case of gillnetters and vessels using hooks and lines, the movement between métiers is restricted by the administrative permissions needed to change métier, which could be denied or delayed in time. However, we have no information to assess the importance of this restriction or to allow it to be included in the model. Furthermore, tradition and risk aversion are important factors that preclude the fishermen changing their behaviour from year to year, as pointed out by various authors (Marchal et al. 2013, van Putten et al. 2012).

On the other hand, variable costs were equal for all the métiers within the same fleet and stock prices were equal for all the métiers and fleets. Hence, the difference in the profitability of the métiers was only driven by the difference in the catch profile and the catchability of the stocks. If the differences in costs and prices among métiers were high, distribution of effort obtained would differ significantly from that obtained here. The effort share in métiers with lower variable costs and/or higher prices would be underestimated and overestimated otherwise.

Need for a different approach to mixed fisheries management

Under the landing obligation, fishing mortalities were, in general, well below the targets, independently of the reference point used. Each fleet had a limiting stock that prevented it from reaching the quotas for the rest of the stocks. Hence, the overall TACs were never reached and fishing opportunities were lost for all of them. In order to ensure the optimum use of fishing opportunities, the landing obligation should be accompanied by a management system that ensures consistency between single-stock TACs.

The inconsistency of TACs and quotas is a problem in mixed fisheries (Ulrich et al. 2011) that could be exacerbated with the implementation of the landing obligation as proven here. In the North sea, single-stock advice is already harmonized, taking into account the mixed fisheries nature of the fishery using the Fcube method (ICES 2014b, Ulrich et al. 2011). However, the multi-stock reference points proposed here are independent of the traditional single-stock advice provided by ICES and their fit within current ICES management framework is complicated. The EC is planning to introduce fishing mortality ranges around the current ICES targets (STECF 2015b). These ranges will provide flexibility to the current European TAC and quota system, which in turn will allow single-stock TACs to be harmonized. Within this new framework, multi-stock reference points have a natural fit. They could be used as management targets in a multi-stock HCR to automatically produce multi-stock TAC advice. But before this, the algorithm used to calculate multi-stock reference points will have to be slightly constrained to ensure the values fall inside the predefined ranges. One of the drawbacks of the multi-stock reference points used here is that they depend on the relative exploitation levels of stocks and hence need to be periodically updated to account for changes in the relative exploitation patterns of the fleets. Garcia et al. (2019b) developed an adaptative multi-stock HCR which solves the problem applying annually a common multiplier to the *status quo* fishing mortalities, which give fishing mortalities within the ranges, to produce single-stock TACs. When there was only a fleet with a single metier the HCR produced catch advice that was consistent among stocks. However, in a complex multi-stock and multi-fleet situation the HCR was not able to completely solve the problem.

Simons et al. (2015) analysed the landing obligation policy using a quantitative multi-stock and multi-fleet bio-economic model. They found that the landing obligation with no exemptions would produce a decrease in the biomass of saithe stock and in the profits of all the fleets. They studied the combination of the landing obligation with exchange rates between cod and saithe quotas and found that the exchange would be beneficial for both fleets and stocks. The different results obtained in both studies highlight the importance of evaluating the impact of the landing obligation at regional level in order to pinpoint case-specific corrective measures to overcome the possible negative effects of the policy.

Chapter 5

Global sensitivity analysis of `FLBEIA` applied to the demersal fishery operating around Iberian coast

- *The preliminary results obtained in the application of the Sobol method were presented in the **ICES annual conference** celebrated in 2016: "Definition of sampling priorities using global sensitivity analysis and management strategy evaluation".*
- *To promote the combination of MSE and GSA we are using the content of this chapter to write a scientific paper that will be sent to the **Methods in Ecology and Evolution** scientific journal: "Potential of applying global sensitivity analysis to fisheries management simulation models".*

5.1 Introduction

In this chapter we applied the guidelines and criteria defined in Chapter 3 to the base case scenario simulated with `FLBEIA` in Chapter 4.

In Section 3.5 we defined a set of guidelines to promote the application of GSA methods to fisheries simulation models. Most of the guidelines were related with effective conditioning of models, i.e., with reduction of the number of input factors through an adequate conditioning. In this chapter we followed those guidelines to condition the implementation of `FLBEIA` model presented in Chapter 4. In this case, we introduced uncertainty in all the input factors, not only in those related to stock-recruitment process as done in Chapter 4.

Once the model was conditioned as described in Section 5.2.1, the Morris method was applied iteratively using an increasing number of trajectories, from 25 to 300. The AEEs were calculated for the set of output variables described in Section 5.2.2, which together summarized the output of the simulation model; five output variables per stock and four per fleet, which resulted in 37 output variables. The selection of input factors in the application of the Morris method was automatized using the selection criterion defined in Section 3.2.1. Afterwards, the convergence of the method was evaluated using the criterion defined in Section 3.2.2. Once convergence was reached the most important factors were identified.

The Sobol variance decomposition method was then applied to the reduced model as described in Section 5.2.1. This model included uncertainty only in the factors identified as the most important by the Morris method. The rest of the factors were fixed to their mean value. The results of the model were summarized using the same output variables employed in the Morris method. The *first-order* and *total-effect* sensitivity indices were calculated for all the output variables. To synthesize the information, the method proposed by Lamboni et al. (2011) was used to compute the *generalised* sensitivity indices, which are analogous to the Sobol importance indices but for the overall variance in all the output variables. Using the *generalised* sensitivity indices, the performance of the selection criterion was compared with the performance of the selection criterion based on *Savage* scores (Campolongo et al. 2007) and the criterion which selects a *fixed number of factors* for each output variable.

The results of the conditioning of the uncertainty and the application of the Morris and Sobol methods were presented in Section 5.3. Then in Section 5.5, the results were discussed in terms of the performance of the selection and convergence criteria defined in this thesis, how the Morris and Sobol method were implemented, and their implications for fisheries modelling and management.

5.2 Methods

5.2.1 Uncertainty conditioning

The scenario with traditional fleet dynamics and without the implementation of landing obligation defined in Chapter 4 was used as the basis for the uncertainty conditioning.

As a general rule, a uniform distribution with a CV equal to 30% and a mean equal to the value used in Garcia et al. (2017a) were used to condition the uncertainty in the input factors. The exceptions were the maturity and retentions ogives, effort share along metiers, and aging error. All the input factors introduced in the GSA are described in Appendix B. Following the recommendations in Saltelli et al. (2010), the unit hypercube was sampled using the Sobol pseudo-random sequences (Sobol 1967) to accelerate the convergence. For univariate input factors, the values were transformed from the unit hypercube to the original space Ω using the inverse transformation method.

Maturity and retention ogives. Maturity and retention ogives are vectors at age which represent the proportion of mature individuals and of fishes retained on board, respectively. The values range from 0 to 1 and are correlated. We modelled the values that differed from 0 and 1 using a Beta distribution, which is commonly used for modelling proportions (Ferrari and Cribari-Neto 2004). We did not introduce uncertainty in the parameters equal to 0 or 1, because in the observed data all the individuals belonged to the same group (mature or immature), i.e., there was no variability. For the remaining age classes, we parametrized the distribution in such a way that the expected value was equal to the value used in Garcia et al. (2017a) and the CV was equal to 30%. The two parameters of the distribution, ϱ_1 and ϱ_2, were given by:

$$\varrho_1 = \frac{1 - mat \cdot (CV^2 + 1)}{CV^2}$$
$$\varrho_2 = \frac{(1 - mat)^2}{mat \cdot CV^2} + (mat - 1)$$

where mat was equal to the observed value and $CV = 0.3$.

Aging error. The aging error was modelled using the matrix Λ defined in Section 3.5.3. In each iteration, the elements were generated using the Dirichlet distribution that is the generalization to multiple dimensions of the Beta distribution. The Dirichlet distribution was conditioned such that the expected probability of assigning age i to a fish of age a was equal to that in the "noise-only, unbiased" matrix proposed by Reeves (2003). The CV of the proportion of fishes aged correctly was equal to 30%. As the variance in the parameters of Dirichlet distribution is constant, when the CV in the fish aged correctly was set, the CV of the rest was derived from it. For each age group a, the parameters of the Dirichlet distribution, $\{\upsilon_i\}_{i=a_0}^{A}$, were given by:

$$
\begin{aligned}
\upsilon_a &= \frac{\left(1-\lambda_{aa}\cdot(1+CV^2)\right)}{CV^2} \\
\upsilon_i &= \lambda_{ai}\frac{\upsilon_a}{\lambda_{aa}} \qquad\qquad\qquad\qquad i = a_0,\ldots,a-1,a+1,\ldots,a_+.
\end{aligned}
$$

where a is the true age and λ_{ai} corresponds to the (ai) element in Λ. As Dirichlet distribution is multivariate, it was not possible to use the inverse transformation method to transform the data from the unit hypercube. Instead, the two step method defined in Devroye (1986) was used. First, each random number was transformed into a Gamma distribution (using first parameter equal to the mean value of the proportion and the second equal to 1). Second, the obtained values were divided by their sum to obtain a Dirichlet random number.

Effort share. The effort share is the proportion of effort that the fleets expend in each metier. We modelled it using the Dirichlet distribution. The distribution was conditioned using the value of the effort share used in Garcia et al. (2017a) and a CV of 30%. The transformation from the unit hypercube to the original domain Ω was done using the procedure described in the previous paragraph.

Stock-recruitment relationship. The stock-recruitment model is a key element in fishery simulation models because it determines, to a great extent, the productivity of the stocks. The associated uncertainty is high and future recruitments are highly unpredictable.

The structure of the stock-recruitment models used to condition the model were the same used in Garcia et al. (2017a). However, in addition to the uncertainty around the stock-recruitment curve considered there, we also introduced variability in the models' parameters.

The joint probability distribution estimated in Cerviño et al. (2013) was used to condition the mean and the correlation of the hake's stock-recruitment parameters. Megrim's recruitment was modelled using a mean recruitment with variability and a fixed breakpoint from where the recruitment level decreased linearly with spawning stock biomass, until zero biomass which produced zero recruitment. For the rest of the stocks a segmented regression model was used. The join probability distribution of the parameters was obtained carrying out a parametric bootstrap of the model residuals of the base fit in Garcia et al. (2017a). As for hake the join probability distribution was used to condition the mean and the correalation of the parameters.

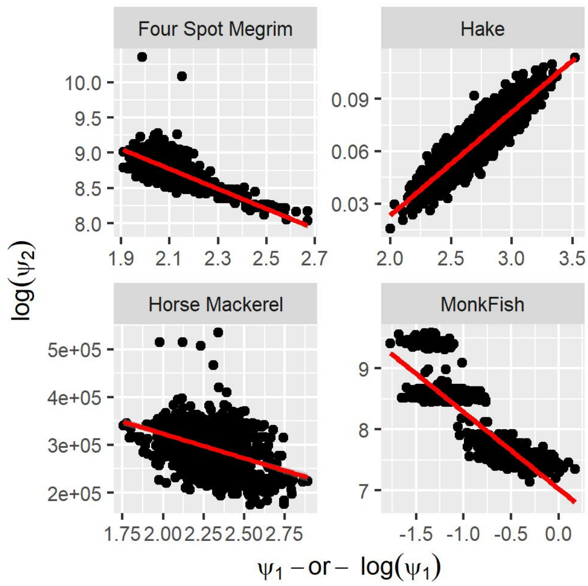

Figure 5.1: Scatter plot of the bootstrap stock-recruitment model parameters. The line corresponds to the linear model fitted to model one parameter, ψ_2, as a function of the other, ψ_1. The 'x' axis corresponds with ψ_1 in the case of hake and horse mackerel and with $\log(\psi_1)$ in the case of four spot megrim and monkfish.

As the parameters of the stock-recruitment relationship tend to be highly correlated (Hilborn, 1992), a linear relationship was used to model the logarithm of one parameter as a function of the other (Figure 5.1). In the GSA, the independent parameter, ψ_1 and the residuals, ϵ, were included as input factors and aggregated in one group. They were conditioned using a uniform distribution with the observed mean value and a CV euqal to 30%.

Observable variables in the management procedure. The maturity and natural mortality were considered constant in the MP using equation (3.10), because usually stock assessment experts consider them constant. With this approach, the natural variability in the input factor generated a departure from the value used in the MP. However, its influence on the results could not be assessed directly, because no associated input factor existed. In fact, the importance of the original factor in the OM was enhanced by its observation error.

For weight at age, we used a quantile transformation to include an observation error independent of age and year. For landings and discards, we introduced a multiplicative error, constant along ages and variable along years. To simulate the error incurred when an assessment model is applied to obtain an estimate of the abundance of the stocks, we introduced an error in the observed abundance. As for landings and discards, the error was constant along ages and variable along years. Furthermore, we introduced an aging error in all the observed variables using the matrix defined in Section 5.2.1.

5.2.2 Output variables

The output of the simulation model was summarized using five output variables per stock and four variables per fleet, which resulted in 37 output variables per year.

The output variables related with the stocks were:

- *Spawning stock biomass* (SSB) which is related with stock abundance;
- *recruitment* which is related with the productivity of the stock;
- *fishing mortality* (F) which is an indicator of exploitation level;
- *catch* which is related with the exploitation and productivity of the stock;
- *total allowable catch (TAC)* which is the output of the decision making process.

The fleets' performance was summarized using:

- *Effort* which represents fleets' activity;
- *profits* which represents fleets' economic performance;
- *gross value added* (GVA) which is a measure of the goods produced by the fishing activity;
- and *capacity* which measures the number of vessels in the fleets.

The sensitivity indices were calculated for each of the output variables. The Morris method was applied to the value of the output variables in the last year of the simulation. However, the sensitivity indices of the Sobol method were calculated for all the years.

5.2.3 Global sensitivity analysis

Morris elementary effects method. First, we generated a set of trajectories, $\mathbb{P}$, along ω. Then, for $r = 25, 50, 100, 150, 200, 250, 300$, the procedure described in Campolongo et al. (2007) was applied to find $\mathbb{P}_r$.

The selection criterion defined in Chapter 3 was applied with the objective of reducing the number of factors to the half, i.e. $K_{EE} = 67$. For the weighting procedure a grid of weights covering the unit hypercube with intervals of 0.01 width was used. As several weight combinations produced the best match with the *visual* selection, the combination with the most similar weights for the three criteria was chosen, i.e, the weights w_1, w_2 and w_3 that minimized the expression $\sum_{i=1}^{i=3}((w_i - 1/3)^2)$.

Sobol variance decomposition method. The Sobol variance decomposition method was applied to the reduced model, i.e the model obtained introducing uncertainty only in the input factors identified as the most important ones by the Morris elementary effect method. In the reduced model, the discarded input factors were fixed to their mean value. The conditioning of the uncertain input factors was exactly the same used in the application of the Morris method.

We analysed the convergence of the Sobol sensitivity indices examining the width of the bootstrap confidence intervals as proposed by Sarrazin et al. (2016). The model was run for a base sample size of $N = 10000$ iterations. The convergence of individual input factors was verified for $N_t = 150, 300, 500, 1000, 1500, 2000, 2500, 3500, 4500, 5500, 7000, 8500, 10000$. As proposed in section 3.5.4, when a factor, X_k, converged, we stopped evaluating the model in the corresponding C_k matrix.

The sensitivity indices were calculated for the 37 output variables defined in Section 5.2.2 and all the simulation years. Moreover, we used the method proposed by Lamboni et al. (2011) to calculate the *generalised* sensitivity indices using all the output variables over all the projection years.

5.3 Results

5.3.1 Conditioning of the model

5.3.1.1 Selection of the coefficient of variation

We evaluated if the input factors selected were sensitive to the CV used to condition the uncertainty, comparing the results obtained with the Morris method with a CV equal to 30%, with those obtained using a CV of 10% and 50%. For $CV = 10\%$ and $CV = 50\%$, we ran the method using 25 trajectories and carried out a bootstrap with 500 iterations. We compared the input factors selected in all the bootstrap iterations using the three CVs. From the 56 factors selected with a CV of 30% (Section 5.3.2), 39 were selected when $CV = 10\%$ and 51 when $CV = 50\%$. `crewshare.dfn`, `crewshare.hok`, `stkN.error.meg` and `q.ho8` were selected with $CV = 30\%$ but not with the other two CVs. The Sobol method showed that the first three were among the least influential input factors (Figure 5.23) and therefore it is not surprising that they were not selected when the CV was changed. There were other input factors not selected with one of the two CVs which were also among the less influential input factors. However, there were also a few input factors not selected with $CV = 0.10\%$ or $CV = 0.50\%$ which where in the top of the ranking obtained with the *generalised total-effects* in the application of the Sobol method, mainly catchability input factors. On the opposite side, there were also input factors selected with $CV = 10\%$ and $CV = 50\%$ but not selected with $CV = 30\%$, some catchabilites and biological input factors. In summary, even if the selected input factors were sensitive to the selection of the CV, the results were quite robust, with a match higher than a 90% between the sets obtained with the three CVs.

5.3.1.2 Vectors at age and grouping of variables

Weight, maturity, and catchability at age for all the main stocks, natural mortality for horse mackerel, and retention ogives of hake and the two megrims were modelled using quantile transformation. With this technique, the 524 factors involved in the vectors at age were reduced to 42 factors.

The grouping of factors reduced the number of effective factors by 91%, from 348 individual factors to 31 groups of factors (Table 5.1). In addition to those proposed in Section 3.5.2, we defined two groups that were specific to this case study: the effort share per fleet and the variability of the TAC of widely distributed stocks. For each stock, the yearly deviations from the mean TAC were grouped to reduce the number of effective factors in the GSA to three.

For the aging errors we used both techniques; we modelled the parameters of the aging error matrix using a Dirichlet distribution and one uniform random number per column in the aging error matrix, and then we group all the random numbers in one single group. The two techniques together generated a save in the number of input factors of 99%, from 652 to 5.

In summary, the number of input factors was reduced by 85%, from 1580 input factors to 135; note that these numbers include the 56 factors that were not part of any vector at age or group. The table in Appendix B contains a description of the 135 input factors.

Table 5.1: Number of individual input factors in the model and effective number of factors considered in the global sensitivity analysis after applying the guidelines proposed in Chapter 3.

Technique	**Number of input factors**	
	Original	**Final**
No Action	56	56
Groups	348	32
Age Models	524	42
Age Models + Groups	652	5
Total	1580	135

5.3.2 Morris elementary effects method

5.3.2.1 Selection and convergence criteria

In the selection criteria the greatest weight, between 0.5 and 0.75, was assigned to *fixed number of factors* criterion, between 0.20 and 0.40 to *factors with high AEE value* criterion, and between 0.05 and 0.35 to *factors distinguished from the others* criterion.

The convergence of the method was assessed using a bootstrap with 500 iterations. The number of factors selected in the 500 iterations increased quickly with the number of trajectories. With 25 trajectories, only 19 factors were selected in all the iterations and with $r = 300$ trajectories this number increased to 50 (Figure 5.2). When the criterion was relaxed to 95% of the iterations (i.e $\nu = 0.95$), for $r = 25$, 42 factors were selected and then the number of factors increased steadily and became stable at 55 factors for $r \geq 200$. The sets $\mathbb{F}_{200}, \mathbb{F}_{250}$, and $\mathbb{F}_{300}$ differed in only one factor. This occurred because the boundary between the most and the least important factors was diffuse. Hence, to be cautious, we used the union criterion for $r \geq 200$, which resulted in the selection of the 56 factors listed in Table 5.3.

The AEEs for each output variable for $r = 300$ are provided as supplementary material in a shiny application (https://aztigps.shinyapps.io/GSAApp/, password: flbeiaGSA. The code used to produce the application is provided in zenodo.org, Garcia et al. (2019b)). In general, for recruitment, SSB, TAC, and number of vessels, there was a set of input factors that were differentiated from the rest because of their high AEE value (see Figures 5.5 to 5.11). However, for the remaining variables the differentiation was not equally clear. For most of the output variables, the difference between the number of input factors selected visually and

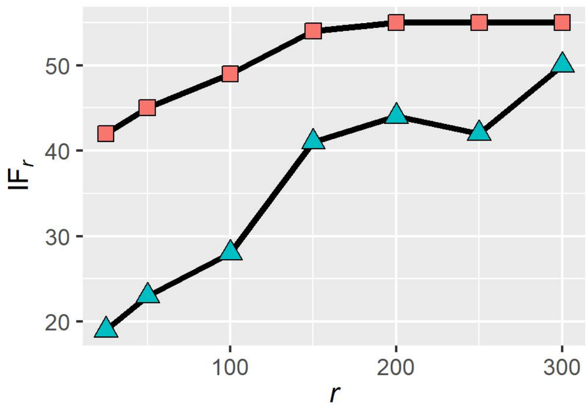

Figure 5.2: Number of factors selected (IF_r) in all the bootstrap iterations (blue and triangle dots) and the number of those selected in 95% of the iterations (red and square dots) as a function of the number of trajectories (r) used in the computation of the elementary effects. Figure taken from Garcia et al. (2019a)

those selected with the *calibrated visual criterion* was equal or lower than one factor (see Table 5.2). Furthermore, the variability in the number of input factors selected was higher for the *visual* criterion. Although variable by variable some differences exist between the *visual* and *calibrated* criteria, as the input factors were aggregated in a single set and the most important input factors appear at the top of many of the variables, at overall level, the differences were small.

The *fixed number of factors* criterion had the highest weight in the definition of *calibrated visual* criterion. However, the number of factors selected with the *calibrated visual* criterion differed from the number of factors selected with the *fixed number of factors* criterion in most of the cases (see Table 5.2). The other two selection criteria had less weight but the number of factors selected with these criteria was more extreme and they deviated the number of factors selected with the *calibrated visual* criterion from those selected with the *fixed number of factors* one (see Table 5.2).

The application of the Morris method resulted in the selection of most of the biological input factors (24 input factors out of 35, 69%). On the contrary only a few economic input factors were selected (5 out of 33, 15%). In the observation error category almost half of the input factors were selected (16 out of 34, 47%) and in the case of technical input factors one third (11 out of 33, 33%). The selected factors are listed in Table 5.3.

Table 5.2: Number of input factors selected by each of the selection criteria for each output variable. The column 'Fixed' corresponds with the *fixed number of factors* criterion, 'High' with the *factors with high AEE value* criterion, 'Diff' with the *factors distinguished from the others* criterion, 'Visual' with the number of factors selected visually and 'Calib.' with the *visual calibrated* criterion. (F = fishing mortality, Rec. = Recruitment, Prof. = Profits, Eff. = Effort, nVes. = Number of vessels, HKE = hake, HOM = horse mackerel, LDB = four spot megrim, MEG = megrim, MON = monkfish, DFN = gillnetters, DTS = trawlers and HOK = longliners). Reprinted from Garcia et al. (2019a).

		Fixed	**High**	**Diff.**	**Vis.**	**Calib.**
SSB	**HKE**	6	5	2	5	5
	HOM	6	2	6	6	5
	LDB	6	5	8	8	6
	MEG	6	5	9	5	6
	MON	6	5	8	8	6
Catch	**HKE**	6	16	5	5	9
	HOM	6	6	11	7	6
	LDB	6	9	1	6	6
	MEG	6	17	9	6	10
	MON	6	12	6	5	8
F	**HKE**	6	19	5	9	10
	HOM	6	7	1	5	6
	LDB	6	10	6	5	7
	MEG	6	9	6	4	7
	MON	6	32	4	14	15
Rec.	**HKE**	6	8	8	6	7
	HOM	6	3	6	6	5
	LDB	6	2	2	7	4
	MEG	6	2	2	2	4
	MON	6	3	4	3	5
TAC	**HKE**	6	8	9	6	7
	HOM	6	5	7	7	6
	LDB	6	5	9	5	6
	MEG	6	7	16	7	7
	MON	6	10	6	5	7
Prof.	**DFN**	6	14	3	8	8
	DTS	6	9	4	12	7
	HOK	6	11	9	8	8
Eff.	**DFN**	6	21	8	8	11
	DTS	6	10	6	10	7
	HOK	6	13	9	8	9
GVA	**DFN**	6	16	1	7	9
	DTS	6	8	6	11	7
	HOK	6	11	3	8	7
Nves.	**DFN**	6	1	5	5	4
	DTS	6	1	1	5	4
	HOK	6	1	4	4	4

Table 5.3: Input factors identified as the most important by Morris elementary effects method. SRR = Stock recruitment relationship, Obs. = Observation, HKE = hake, HOM = horse mackerel, LDB = four spot megrim, MEG = megrim, MON = monkfish, PTB = Pair trawlers, DTS = Trawlers. = four spot megrim, MEG = megrim, MON = monkfish, DFN = gillnetters, DTS = trawlers and HOK = longliners). Reprinted from Garcia et al. (2019a).

Stock Level	
Factors	**Stock**
Aging error	all
Maturity	HKE, MON
Natural mortality	all
Weight	all
Initial population	HKE, HOM
SRR parameters	all
Uncertainty around SRR	all
Obs. error in abundance	HKE, HOM, MEG, MON
Obs.error in weight	all
TAC	MAC, HO8

Fleet Level	
Factor	Fleet
Crewshare	ALL
Effortshare	ALL
FuelCost	DTS
Maximum days at sea	ALL
w1	DTS

	Fleet-Metier and Stock level	
Factor	**Stock**	**Fleet-metier**
Cachability	HKE	PTB metier in DTS SP
Cachability	HO8, LDB, MAC, MEG	all

5.3.2.2 Absolute elementary effects

The 15 factors with the highest AEE value for each output variable and stock or fleet are shown in Figures 5.3 to 5.11, which we will comment one by one below.

Catch (Figure 5.3). For the two megrims and monkfish the factors with the highest AEE were the natural mortality, the weight, the uncertainty around the stock-recruitment curve and the effort share of trawlers (not necessarily in this order). For the two megrims the catchability of western horse mackerel and its TAC had also a high AEE. After those factors the value of the AEEs decreased steadily. For hake the factors that differentiated somewhat from the rest were natural mortality, the effort share of trawlers and weight. For horse mackerel, weight and natural mortality differentiated clearly from the rest and then there was a second group with the errors in the assessment, the initial abundance and the uncertainty around the stock-recruitment curve.

Fishing mortality (Figure 5.4). For all the stocks but horse mackerel the factor with the highest AEE value was the effort share of trawlers. The second one was the catchability of western horse mackerel for hake and the two megrims. For hake, the AEE of the rest of the factors decreased steadily without forming groups. For the megrims four factors differentiated from the rest which were the two already mentioned, their catchability and the TAC of western horse mackerel. For monkfish the value of all the AEEs decreased steadily without forming groups. For horse mackerel the weight, the natural mortality and the errors in the assessment (weight, aging error and abundance) were the factors which AEEs differentiated from the rest.

Recruitment (Figure 5.5). For all the stocks except hake the parameters of the stock-recruitment relationship and the uncertainty around the stock-recruitment curve were the factors with the highest AEEs. For monkfish, besides those two factors, maturity had also a high AEE value and for horse mackerel weight and natural mortality. In the case of hake, there was not a clear differentiation of the factors with high and low AEE value. Among the most important were natural mortality, the parameters of the stock-recruitment relationship and the uncertainty around it, the effort share of trawlers, weight and maturity.

Spawning stock biomass (Figure 5.6). For hake and the two megrims the four factors with the highest AEE were weight, natural mortality, the effort share of trawlers and the uncertainty around the stock-recruitment curve. For monkfish, the maturity replaced the effort share of trawlers in the group of the four most important factors. Besides, for the two megrims the catchability was the factor with the 5-th highest AEE value and the value of the 6-th was significantly lower. Something similar happened for hake for which the 5-th with the highest value was maturity. For horse mackerel the AEE of natural mortality and weight differentiated clearly from the rest of the AEEs.

Total allowable catch (Figure 5.7). The errors in the assessment were among the factors with the highest AEE value for all the stocks. Besides, for hake, weight,

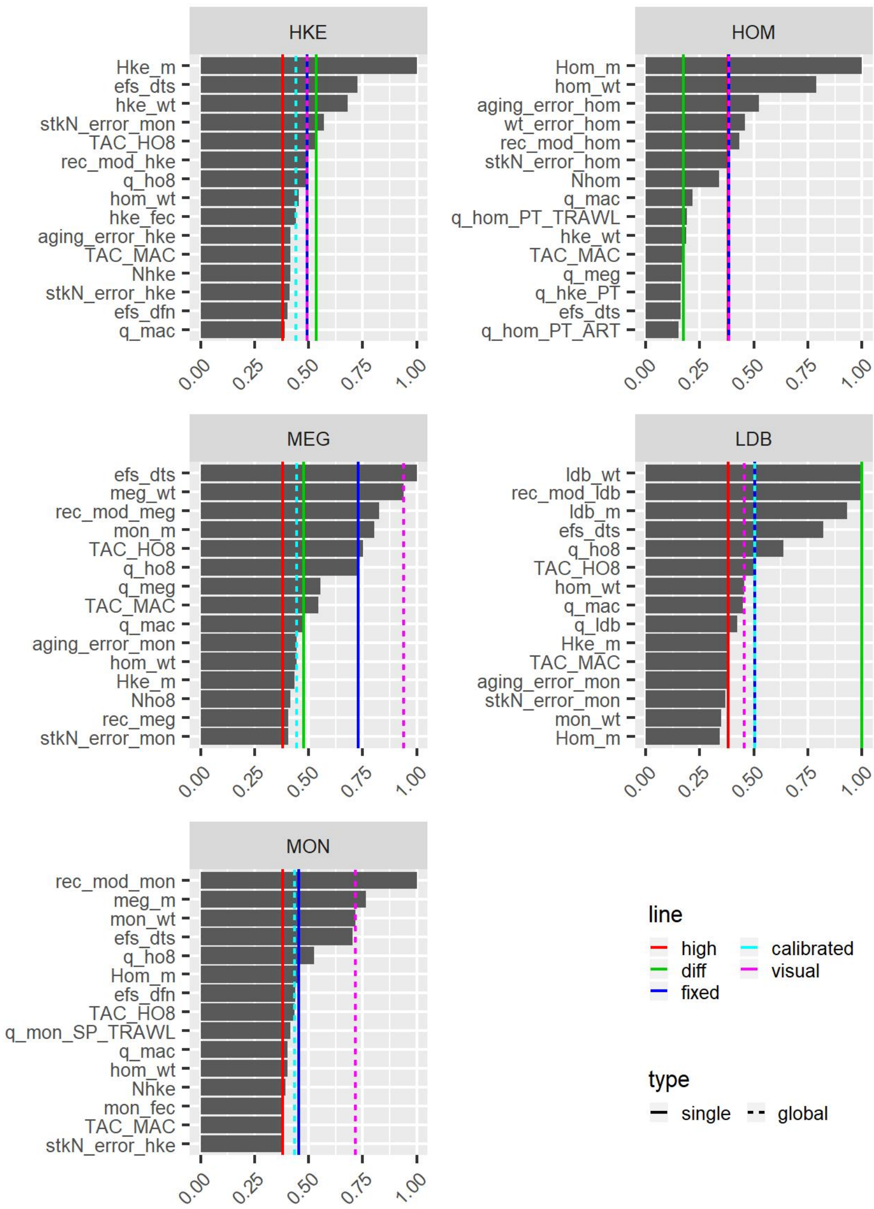

Figure 5.3: Barplot with the AEE of **catch** for each of the stocks. The vertical lines indicate the factors selected by each selection criteria: *fixed number of factors* (blue), *factors distinguished from the others* (green), *factors with high AEE value* (red), the *visual selection* (pink) and the *calibrated visual* criterion (light blue). Solid and dashed lines differentiate between the criterion based on a single rule defined in chapter 3 (solid line) and the *visual* and *calibrated visual* criteria (dashed line).

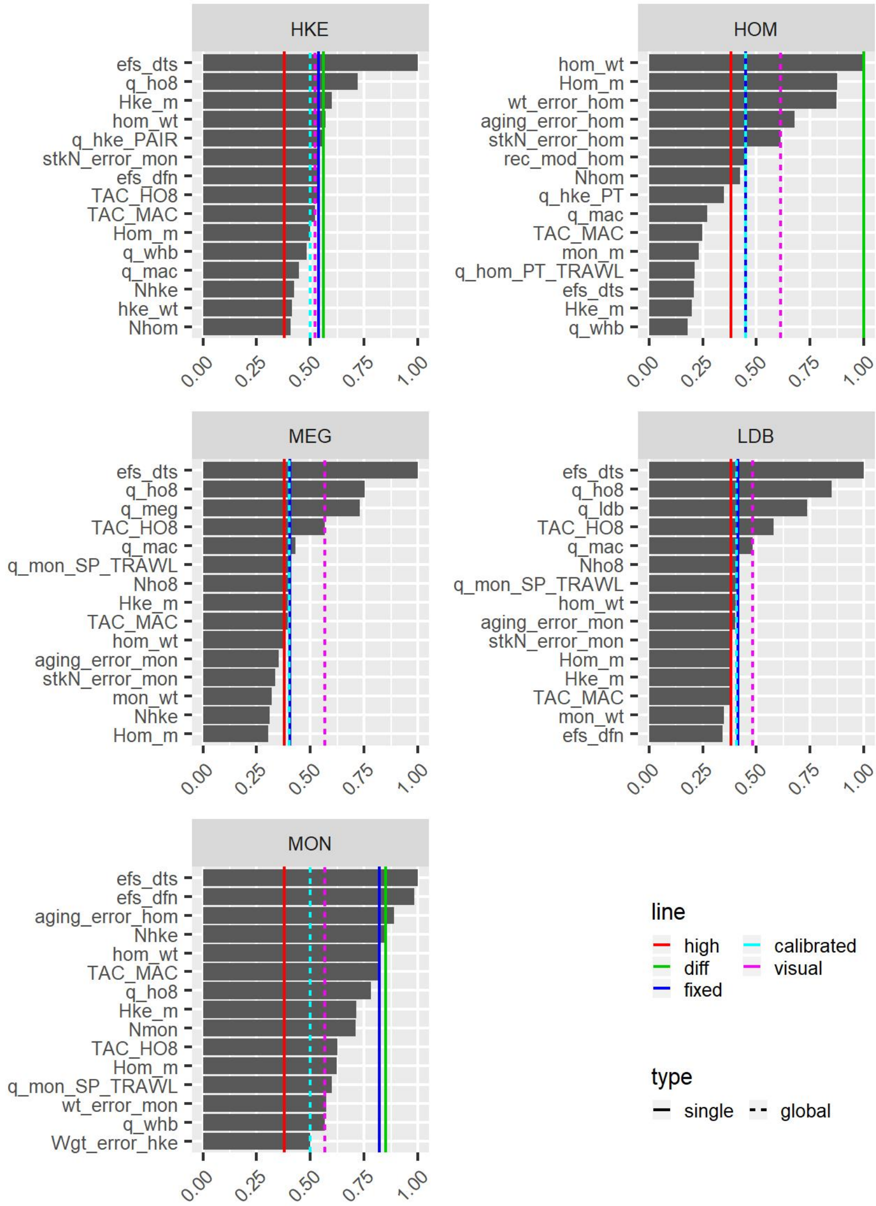

Figure 5.4: Barplot with the AEE of **fishing mortality (F)** for each of the stocks. The vertical lines indicate the factors selected by each selection criteria: *fixed number of factors* (blue), *factors distinguished from the others* (green), *factors with high AEE value* (red), the *visual* selection (pink) and the *calibrated visual* criterion (light blue). Solid and dashed lines differentiate between the criterion based on a single rule defined in chapter 3 (solid line) and the *visual* and *calibrated visual* criteria (dashed line).

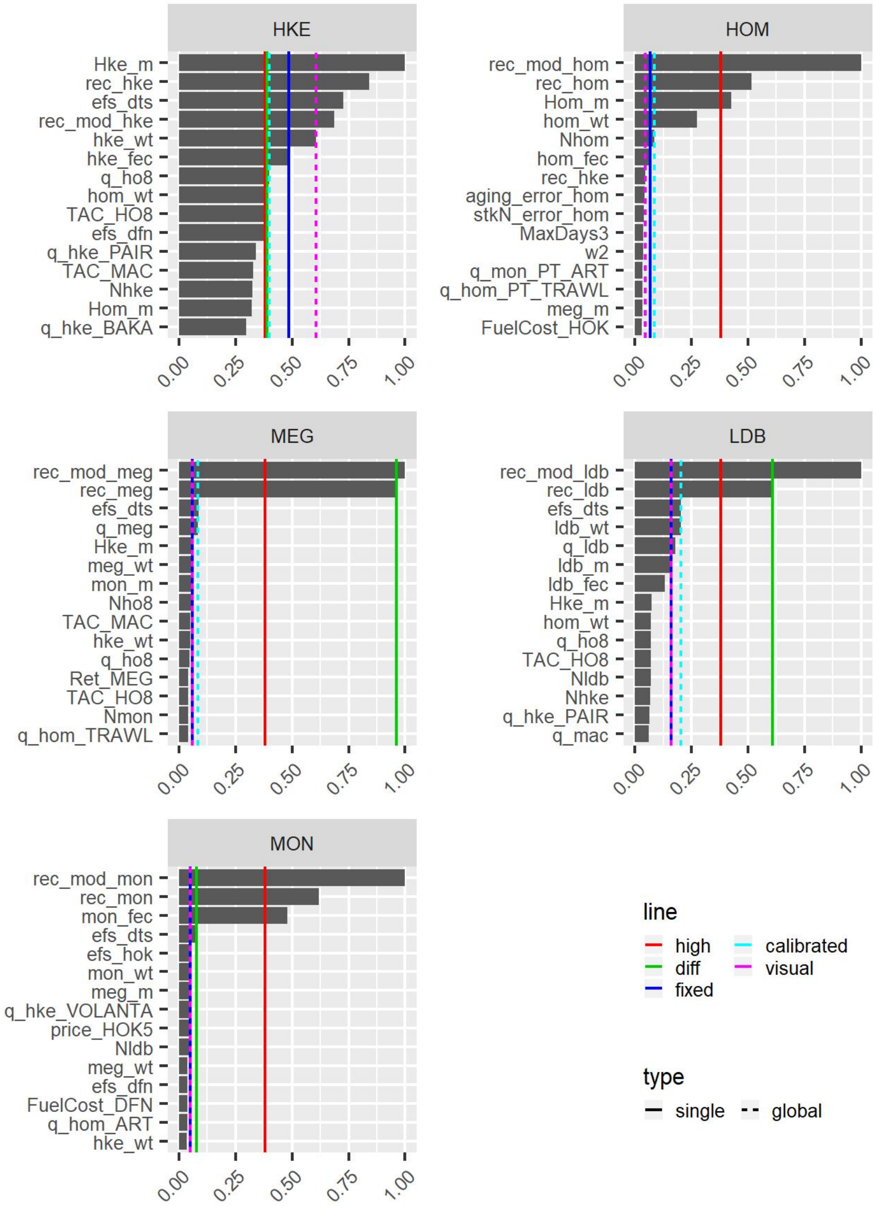

Figure 5.5: Barplot with the AEE of **recruitment** for each of the stocks. The vertical lines indicate the factors selected by each selection criteria: *fixed number of factors* (blue), *factors distinguished from the others* (green), *factors with high AEE value* (red), the *visual* selection (pink) and the *calibrated visual* criterion (light blue). Solid and dashed lines differentiate between the criterion based on a single rule defined in chapter 3 (solid line) and the *visual* and *calibrated visual* criteria (dashed line).

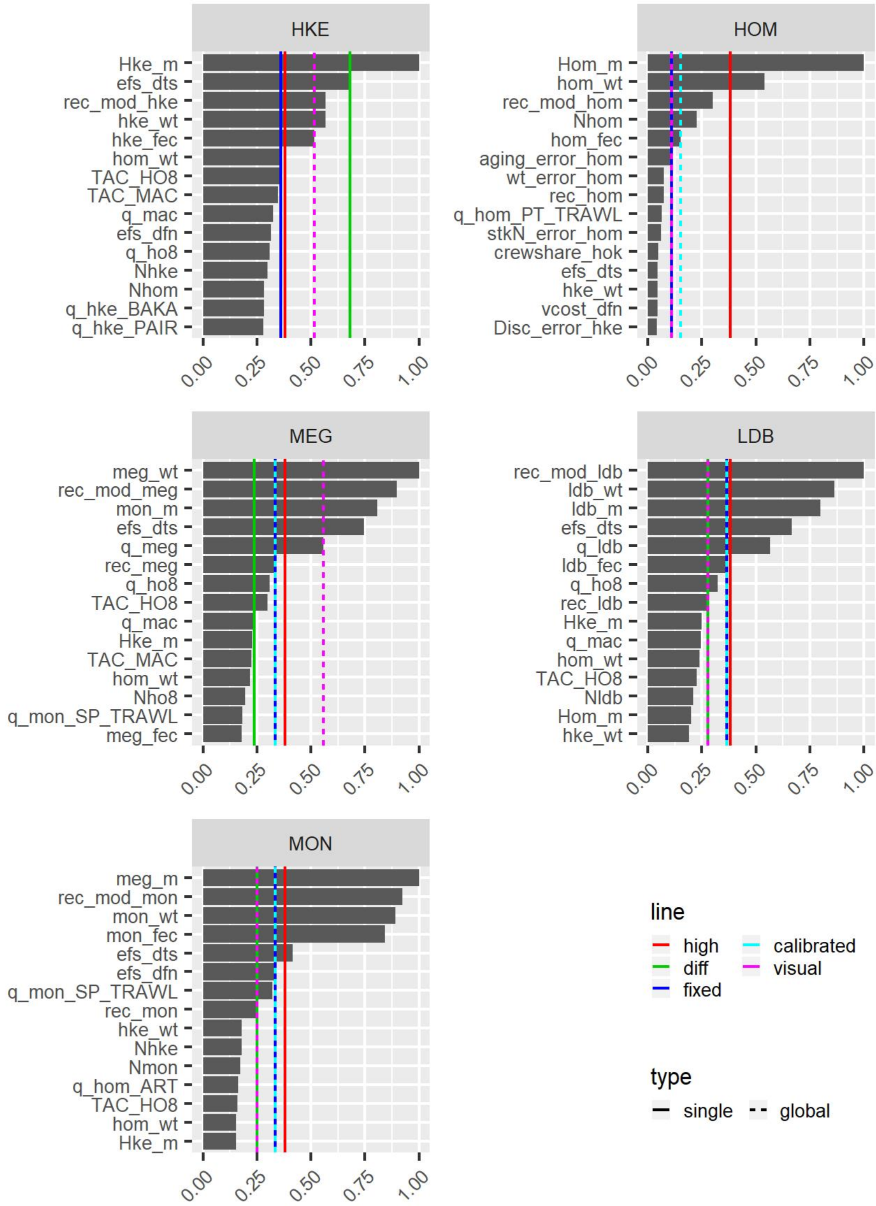

Figure 5.6: Barplot with the AEE of **spawning stock biomass (SSB)** for each of the stocks. The vertical lines indicate the factors selected by each selection criteria: *fixed number of factors* (blue), *factors distinguished from the others* (green), *factors with high AEE value* (red), the *visual* selection (pink) and the *calibrated visual* criterion (light blue). Solid and dashed lines differentiate between the criterion based on a single rule defined in chapter 3 (solid line) and the *visual* and *calibrated visual* criteria (dashed line).

natural mortality and effort share of trawlers were in the group of factors that differentiated from the others. For horse mackerel the factors with highest AEE were exactly the same as in the case of catch. For megrim, the weight and the effort share were also in the group of the factors with highest AEE value. For four spot megrim, the uncertainty around the stock-recruitment curve and the natural mortality closed the group of the five factors with highest AEE value. In the case of monkfish the group was complemented by the uncertainty around the stock-recruitment curve and the weight.

Effort, gross value added and profits (Figures 5.8, 5.9 and 5.10). The relative value of the AEEs for effort, GVA and profits output variables was similar but with different scale. The factors with the highest AEEs were the same and their order, from the highest AEE to the lowest, was similar. Furthermore, the difference between consecutive AEEs was similar. For the three fleets the factor with the highest AEE was their effort share. For trawlers the catchability and the TAC of western horse mackerel were in the second and third position, respectively. For gillnetters, the observation error in the abundance of monkfish, the effort share of trawlers and the natural mortality of hake were in the highest positions. Finally, in the case of longliners, the observation error in the weight and abundance of hake were the most important ones after effort share.

Number of vessels (Figure 5.11). In the number of vessels variable, for all the fleets, the maximum number of days that each vessel operates yearly was the factor with highest AEE value. Furthermore, the difference with the AEE value of the rest of the factors was big. The proportion of income used to pay salaries, the proportion of profits invested in buying new vessels and effort share were in the first positions for the three fleets; however, in comparison with the AEE value of maximum days, the value of the AEE of these factors was negligible.

5.3.3 Sobol variance decomposition method

5.3.3.1 General patterns

We analysed the convergence of the Sobol sensitivity indices examining the width of the bootstrap confidence intervals as proposed by Sarrazin et al. (2016). The width decreased rapidly with N for $N < 2000$ (Figure 5.12). For $N = 150$, the width of the confidence interval of the *total-effect* index of all the input factors and

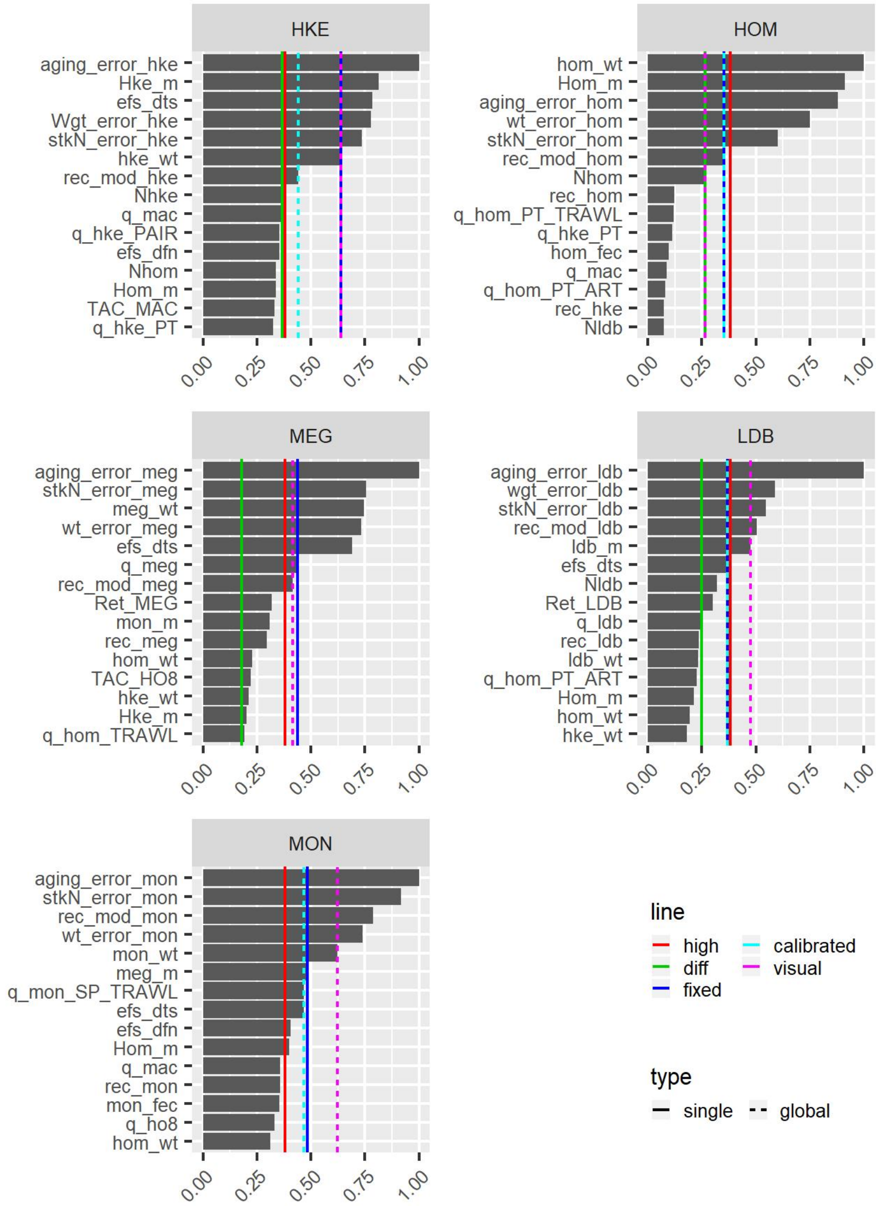

Figure 5.7: Barplot with the AEE of **total allowable catch (TAC)** for each of the stocks. The vertical lines indicate the factors selected by each selection criteria: *fixed number of factors* (blue), *factors distinguished from the others* (green), *factors with high AEE value* (red), the *visual selection* (pink) and the *calibrated visual* criterion (light blue). Solid and dashed lines differentiate between the criterion based on a single rule defined in chapter 3 (solid line) and the *visual* and *calibrated visual* criteria (dashed line).

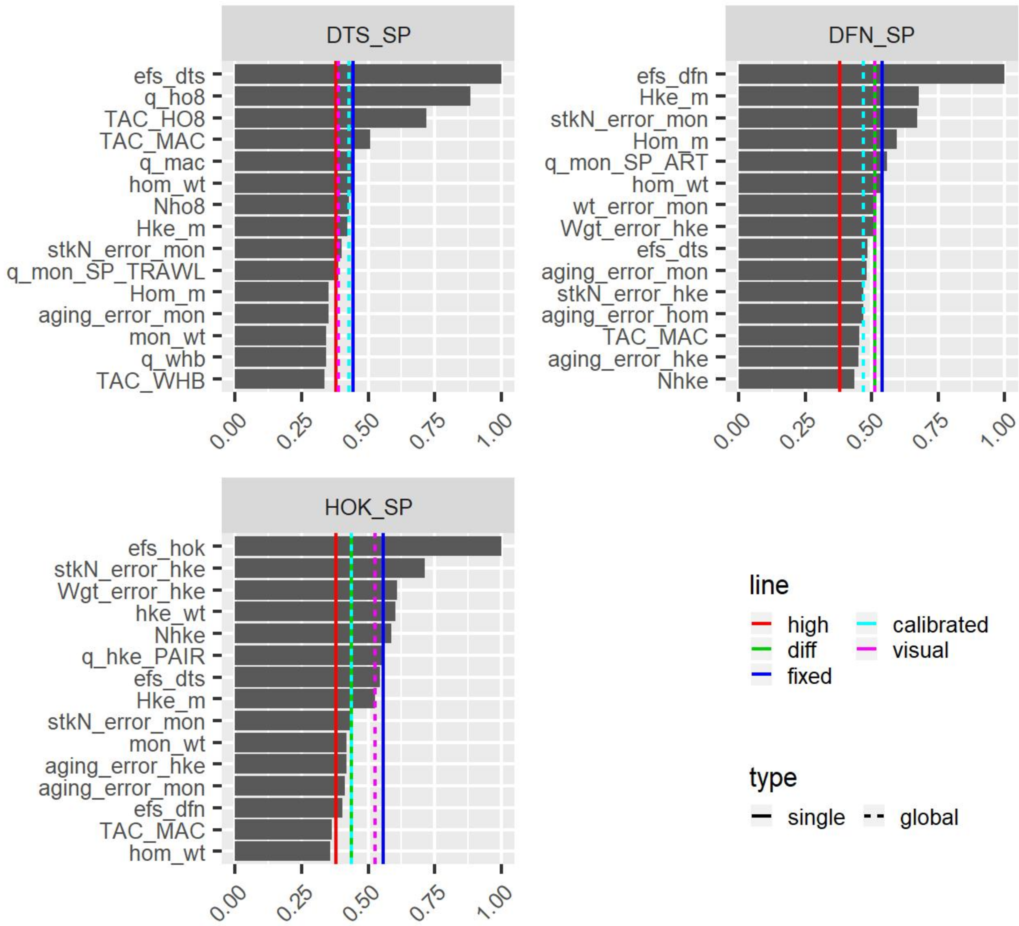

Figure 5.8: Barplot with the AEE of **effort** for each of the fleets. The vertical lines indicate the factors selected by each selection criteria: *fixed number of factors* (blue), *factors distinguished from the others* (green), *factors with high AEE value* (red), the *visual selection* (pink) and the *calibrated visual* criterion (light blue). Solid and dashed lines differentiate between the criterion based on a single rule defined in chapter 3 (solid line) and the *visual* and *calibrated visual* criteria (dashed line).

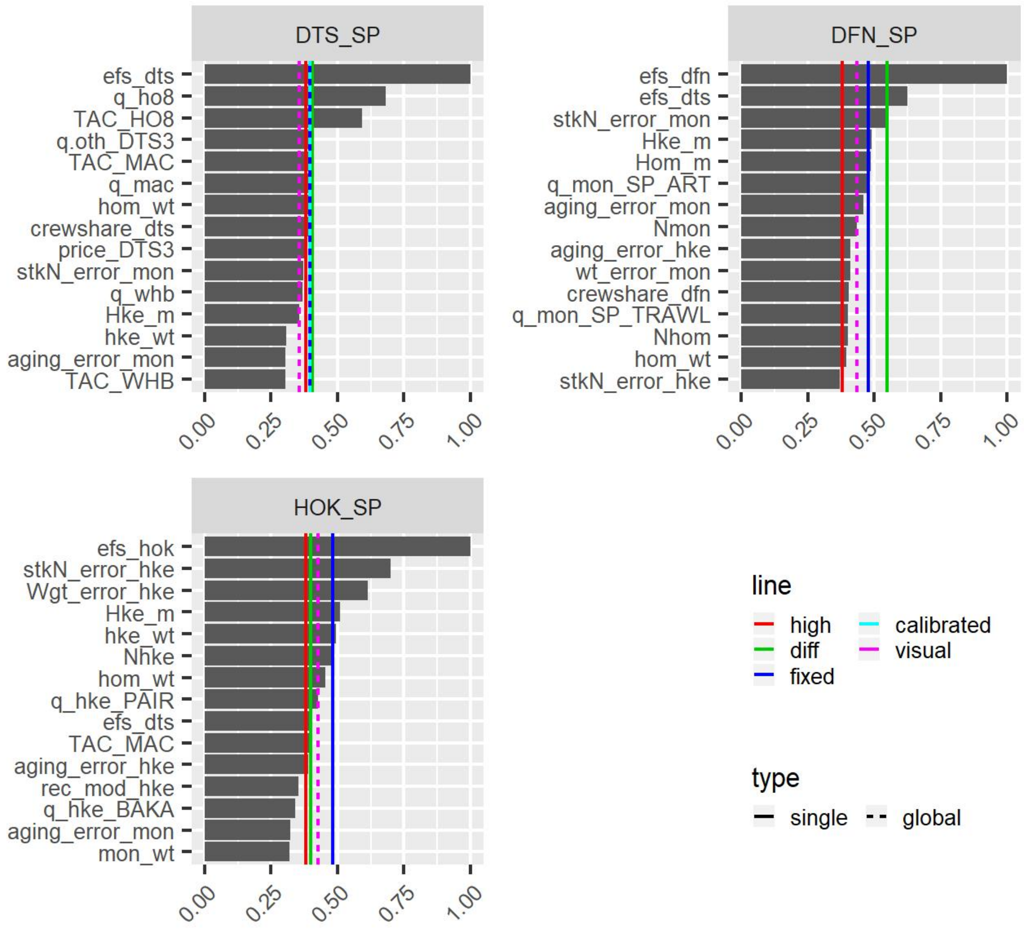

Figure 5.9: Barplot with the AEE of **profits** for each of the fleets. The vertical lines indicate the factors selected by each selection criteria: *fixed number of factors* (blue), *factors distinguished from the others* (green), *factors with high AEE value* (red), the *visual selection* (pink) and the *calibrated visual* criterion (light blue). Solid and dashed lines differentiate between the criterion based on a single rule defined in chapter 3 (solid line) and the *visual* and *calibrated visual* criteria (dashed line).

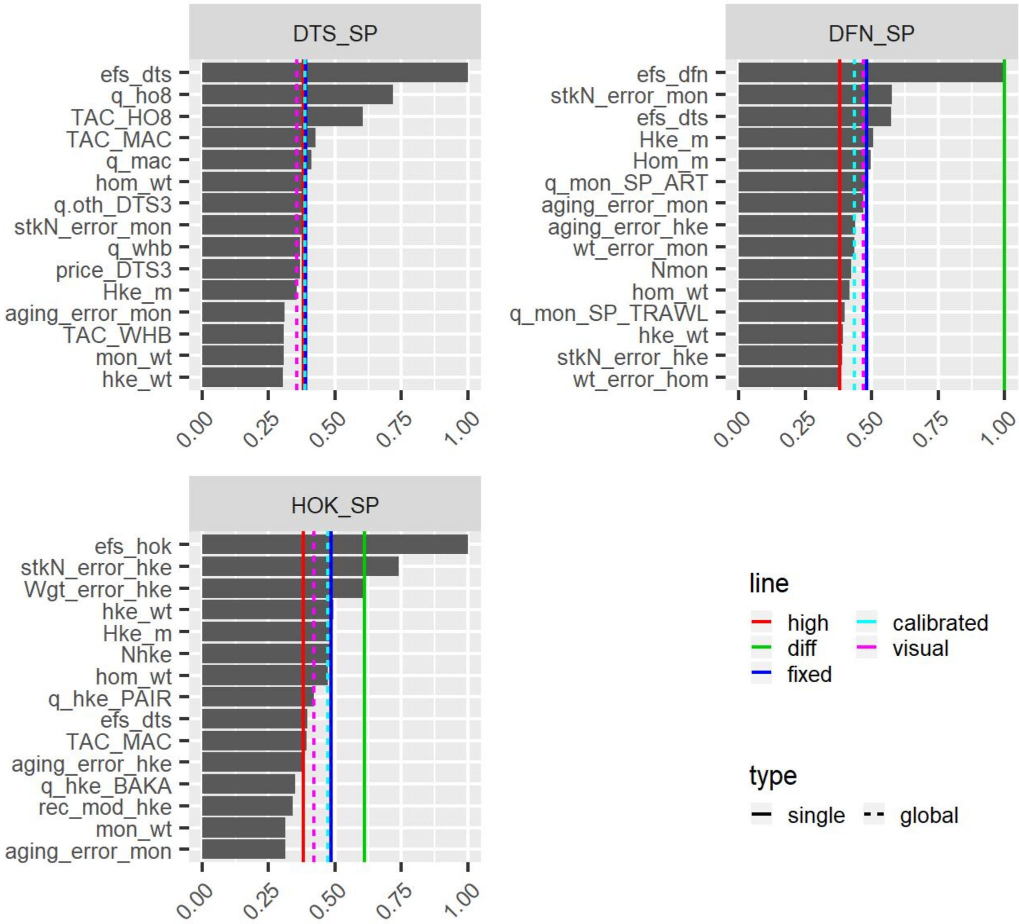

Figure 5.10: Barplot with the AEE of **gross value added (GVA)** for each of the fleets. The vertical lines indicate the factors selected by each selection criteria: *fixed number of factors* (blue), *factors distinguished from the others* (green), *factors with high AEE value* (red), the *visual selection* (pink) and the *calibrated visual* criterion (light blue). Solid and dashed lines differentiate between the criterion based on a single rule defined in chapter 3 (solid line) and the *visual* and *calibrated visual* criteria (dashed line).

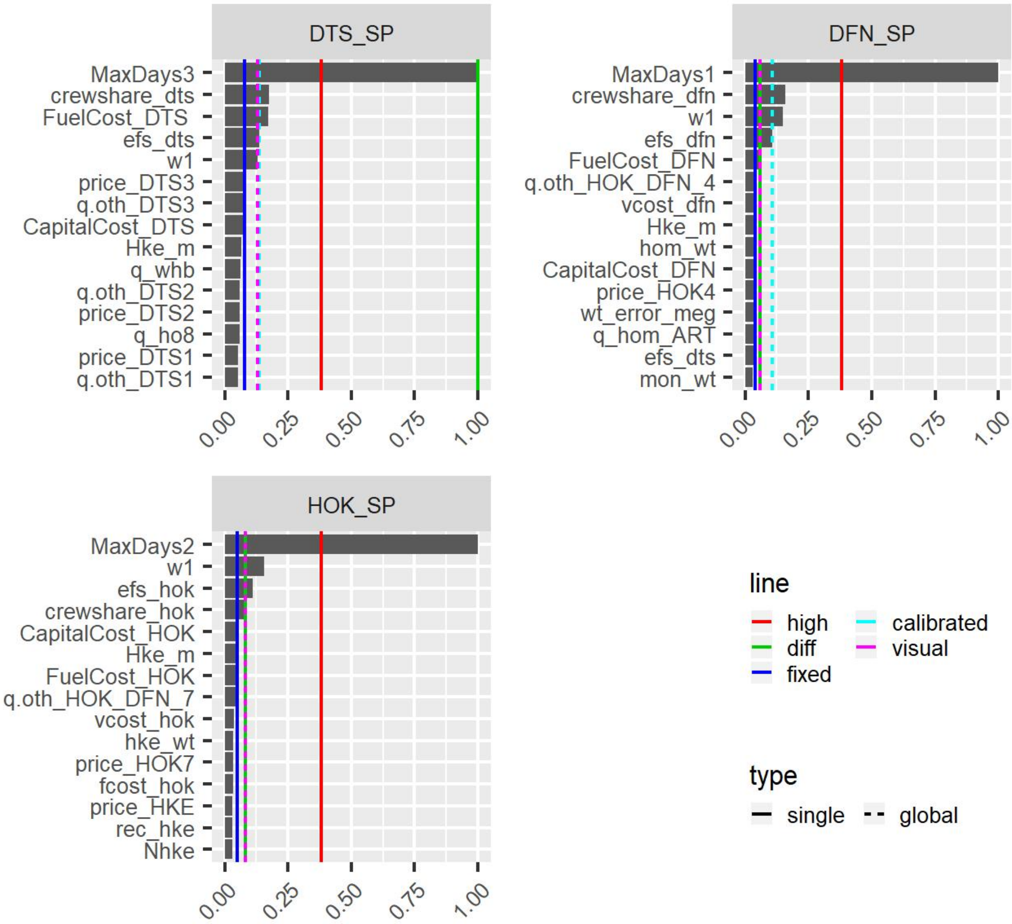

Figure 5.11: Barplot with the AEE of **number of vessels** for each of the fleets. The vertical lines indicate the factors selected by each selection criteria: *fixed number of factors* (blue), *factors distinguished from the others* (green), *factors with high AEE value* (red), the *visual selection* (pink) and the *calibrated visual* criterion (light blue). Solid and dashed lines differentiate between the criterion based on a single rule defined in chapter 3 (solid line) and the *visual* and *calibrated visual* criteria (dashed line).

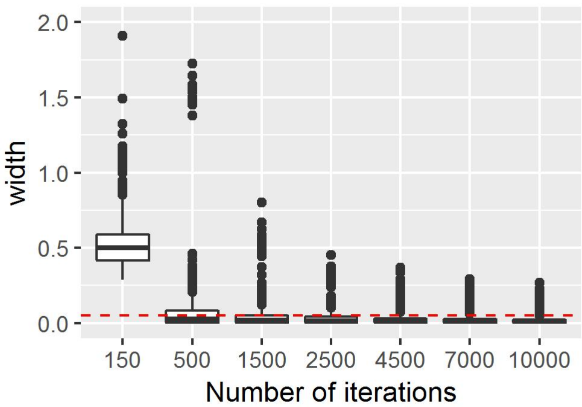

Figure 5.12: Boxplot of the width of the confidence intervals of the *total-effect* index for all the input factors and output variables in 2020. The x-axis correspond with the base sample size N used. Figure taken from Garcia et al. (2019a)

output variables in 2020 was greater than 0.5, but for $N = 1500$, 75% of the intervals were already narrower than 0.05. However, the convergence rate slowed down for $N \geq 2000$ and for $N = 10000$ the confidence interval of 4% of the *total-effects* over all the input factors and for all the output variables were wider than 0.05.

When a factor, X_k, converged, we stopped evaluating the model in the corresponding A_k^B matrix. We assessed the convergence of the factors for several base samples from $N = 150$ to $N = 10000$. For $N = 300$, 3 input factors had already converged in all the output variables and for $N = 8500$, 19 input factors (Table 5.4), which led to a 21% saving in model evaluations. The remaining 37 input factors had a confidence interval wider than 0.05 for at least one of the output variables. These input factors corresponded with those which had the biggest impact on the variance of the output variables.

Table 5.4: Number of factors (Nb. Factors) that converged for each base sample N.

N	**Nb. Factors**	**N**	**Nb. Factors**
150	0	3500	14
300	3	4500	15
1000	3	5500	16
1500	5	7000	17
2000	6	8500	19
2500	7	10000	19

In the first year of the simulation, the importance of the *first-order* indices was prevalent, but it decreased with years in favor of the *total-effects* (Figure 5.13). The importance of the interactions was especially marked in the output variables related to the fleets' activity (Figure 5.14).

The results were fleet- and stock-dependent (Figure 5.14). While a great part of the variance in horse mackerel output variables was explained by few input factors, the variance of hake's output variables was the consequence of the variance in many input factors. The same happened with the variance of the output variables related with the fleets' activity, except number of vessels. For example, in trawler fleet most of the factors ($> 80\%$) had a total effect higher than 5%.

The variance explained by *first-order* indices was disaggregated in the variance derived from natural and epistemic variability (Figure 5.15). The effect of epistemic variability in biological output variables was marginal. In contrast, the variability in TAC was largely explained by epistemic variability, which explained between 25% and 40% of the variability. The effect of epistemic uncertainty in effort and related output variables was also relevant. As the variance in the graph refers only to *first-order* variance, the contribution of the epistemic variance is expected to be higher due to the contribution of interactions in the output variance.

A complete set of barplots with the *first-order* and *total-effect* indices and their confidence intervals is available in a shiny application (https://aztigps.shinyapps.io/GSAApp/, password: flbeiaGSA. The code used to produce the application is provided in zenodo.org, Garcia et al. (2019b)).

The plots with the 15 factors with the highest *total-effect* index for each output variable and stock or fleet are shown in Figures 5.19 to 5.22.

5.3.3.2 Stock level

While for hake most of the factors had a significant *total-effect*, for horse mackerel the variance was mainly derived from *first-order* effects. Recruitment was the only output variable where *first-order* effects were predominant for all the stocks. The economic factors did not have any significant impact on the stock output variables.

Catch (Figure 5.16). In the year 2013, the variability of catch was explained by the direct effect of few factors. However, in the second year the number of factors contributing to the variance increased significantly and in 2020 most of the variance was explained by the interaction of two or more factors (Figure 5.16). Natural mortality and weight were among the most important factors for all the stocks. Furthermore, there were seven factors that appeared in the top 15 of all the stocks

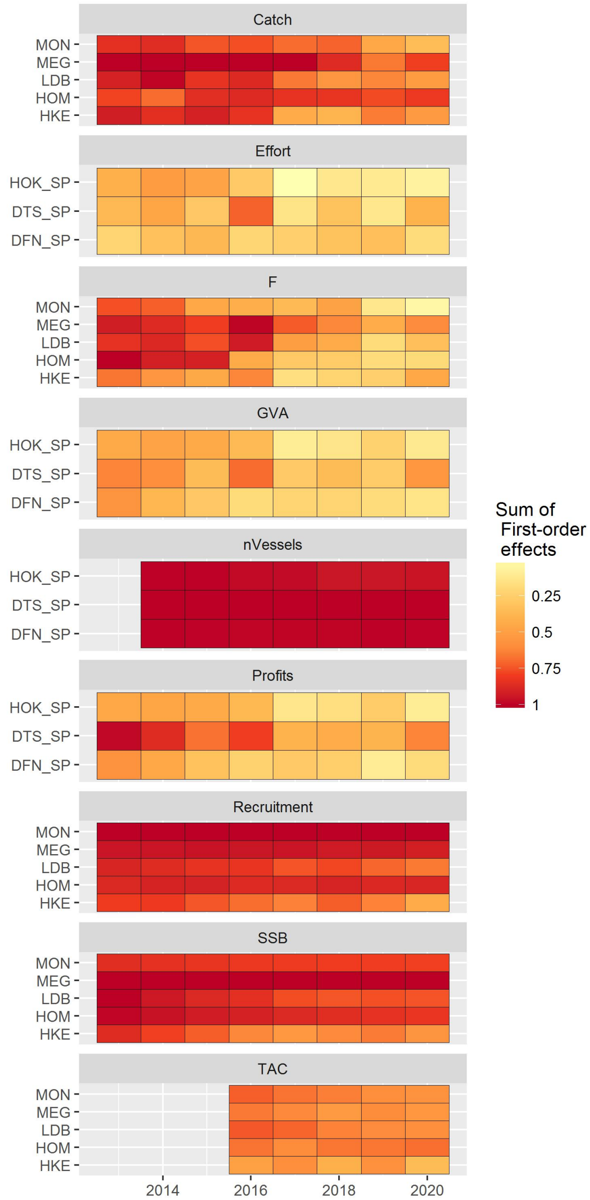

Figure 5.13: Total variance explained by *first-order* indices for each of the output variables and stock or fleet along years. Light yellow represents 0 and dark red 1.

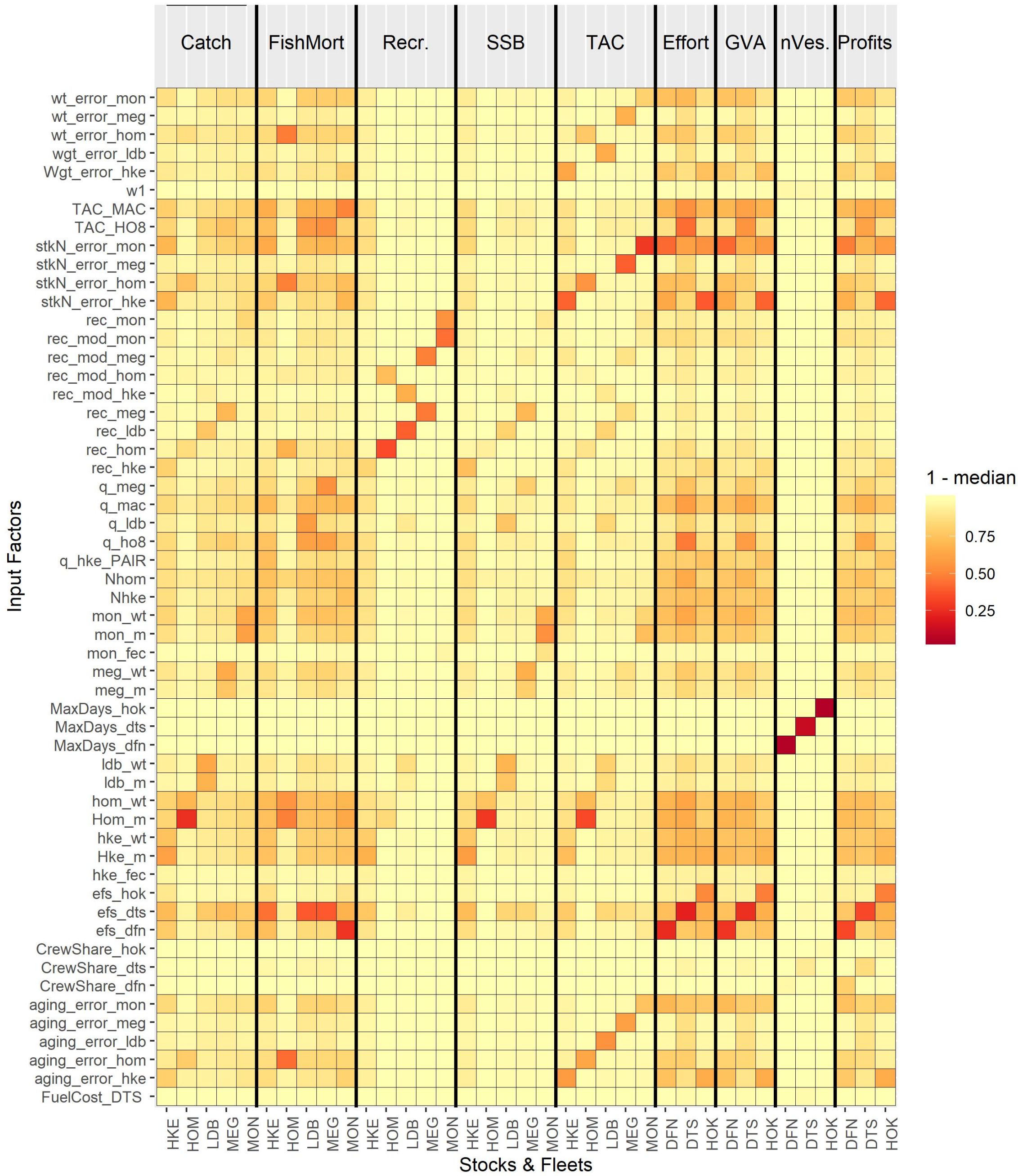

Figure 5.14: Variance explained by *total-effects* for all the output variables in 2020 year. Light yellow represents 0 and dark red 1. (FishMort = Fishing mortality, Recr. = Recruitment and nVes. = Number of vessels). Figure taken from Garcia et al. (2019a)

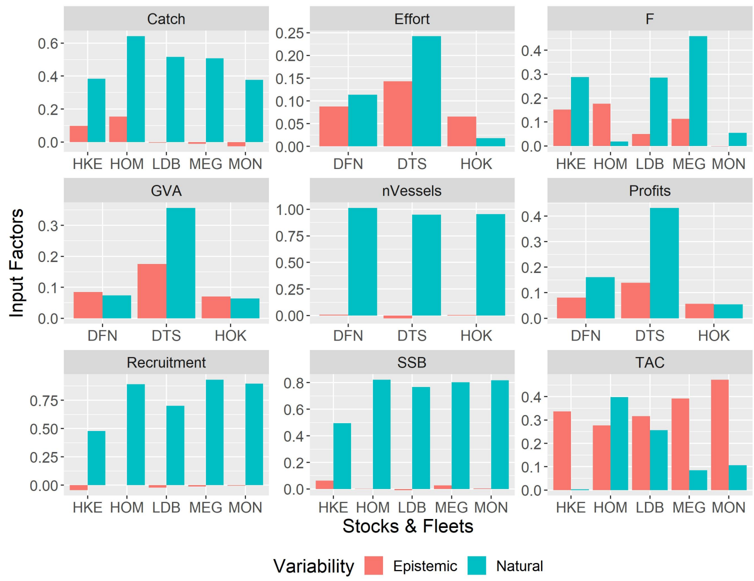

Figure 5.15: Sum of the proportion of variability explained by *first-order* effects disaggregated by the source of variability, *natural* (blue bars) or *epistemic* (red bars).

but horse mackerel (`efs_dts`, `stkN_error_mon`, `TAC_HO8`, `q_mac`, `Hom_wt`, `TAC_MAC` and `Hom_m`). Most of the variability in the catch of horse mackerel was explained by few factors directly related with the stock. For the rest of the stocks some additional factors not directly related with the stock itself contributed significantly to the variance. The variance in the catch of the two megrims had similar decomposition as a function of the variability of the input factors. In 2020, the variance associated to *first-order* effects was higher than 50% for the two megrims and horse mackerel and lower than 25% for hake and monkfish.

Fishing mortality (Figure 5.17). The variance in fishing mortality, except in the case of horse mackerel, was explained by the variance of many factors (Figure 5.17). More than half of the factors considered in the variance decomposition method contributed significantly to the variance of fishing mortality of those stocks. In the top 15, eleven factors were common to all of those stocks (`Nhom`, `Hke_m`, `Hom_m`, `hke_wt`, `hom_wt`, `mon_wt`, `efs_dts`, `q_mac`, `q_ho8`, `stkN_error_mon` and `TAC_MAC`). In the case of horse mackerel six were the factors that had a significant contribution in the variance of its fishing mortality, the three errors in the assessment, weight and mortality, stock-recruitment parameters and initial abundance of

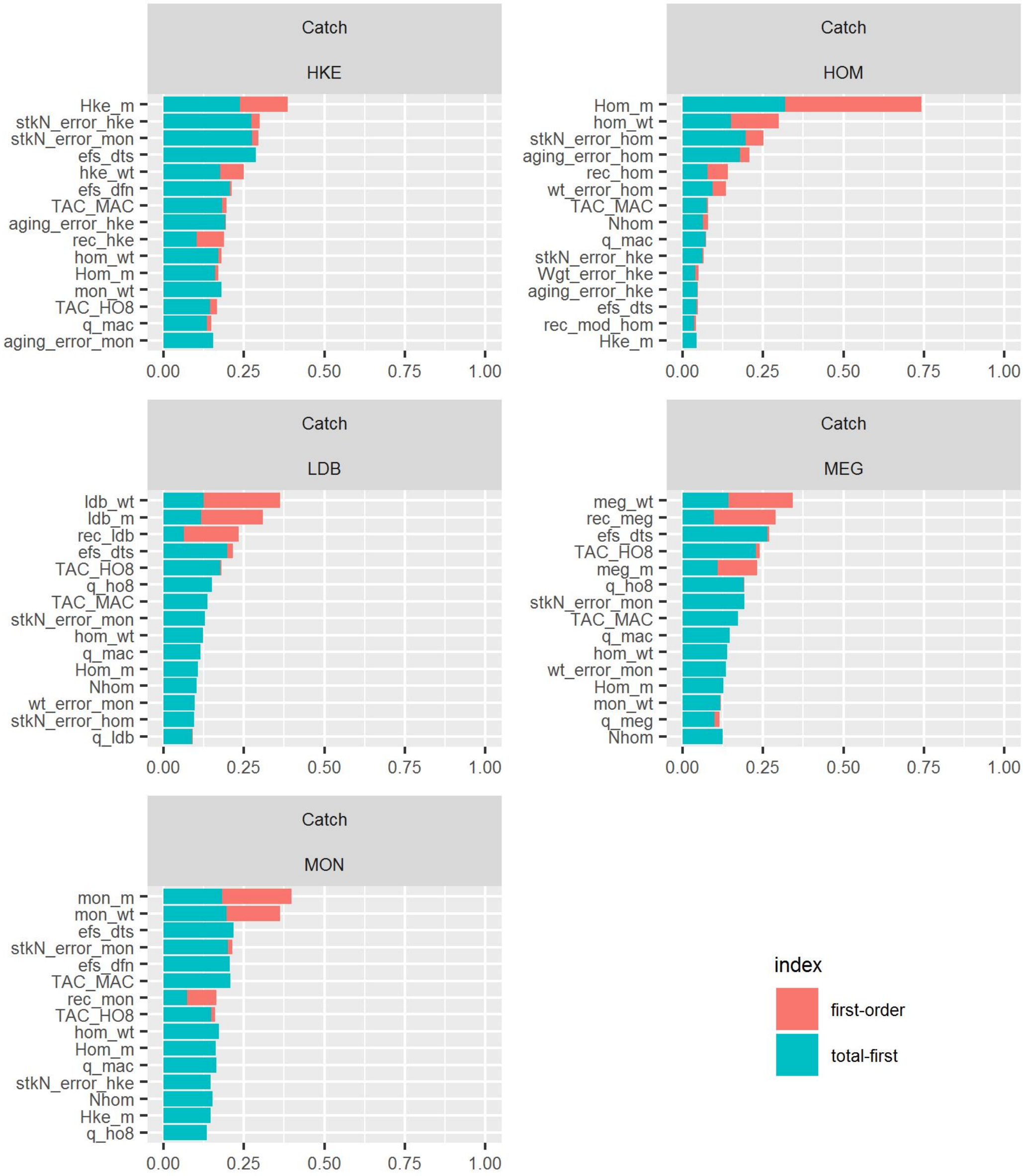

Figure 5.16: Sobol *first-order* and *total-effect* indices for **catch** of all the stocks. Only the 15 factors with highest total index are shown. The red part corresponds with *first-order* index and the entire bar (blue + red) with the *total-effect*.

the stock itself in all the cases.

Recruitment (Figure 5.18). The variability in recruitment, except for hake, was explained almost completely by the variability in the stock-recruitment model parameters and the variability around stock-recruitment model curve (Figure 5.18). Moreover, the effect of interactions was marginal. In the case of hake, the uncertainty in the stock-recruitment model parameters was the most important factor, explaining around 35% of the variance. Other 10% of the variance was explained by the direct impact of several factors. However, the rest of the variance was explained through the interaction of a great number of factors, the most important being natural mortality and weight of hake, and effort share of trawlers.

Spawning stock biomass (Figure 5.19). Most of the variability in SSB was explained by less than five factors for all the stocks but hake (Figure 5.19). For hake, the impact of interactions was high and there were many factors contributing to the variance of its SSB. The most important were the natural mortality, the effort share of trawlers, the stock-recruitment parameters and its weight. The variance of horse mackerel's and monkfish's SSB was explained mostly by the variability in natural mortality and weight. Moreover, the effect of interactions was marginal. For the two megrims, the most important factors were the weight, the natural mortality, the catchability, the stock-recruitment parameters and the effort share of trawlers (not necessarily in this order). For these two stocks the impact of interactions was higher than in the case of horse mackerel or monkfish but lower than in the case of hake.

Total allowable catch. Except in the case of hake the variance in the TAC was produced by the variability in less than 10 factors. The three errors in the management procedure were the most influential factors in the TAC followed by natural mortality and weight. Recruitment model parameters, effort share in trawlers and some of the catchabilities were also important. In the case of hake there were more than 20 factors that contributed significantly to its variance.

5.3.3.3 Fleet level

At fleet level the variance of the output variables was derived mainly from interaction between factors. In 2013 the variance was explained by few factors but from the second year of the simulation the number of factors with significant impact on the results increased. In the long-term around two thirds of the factors had *total-effect*

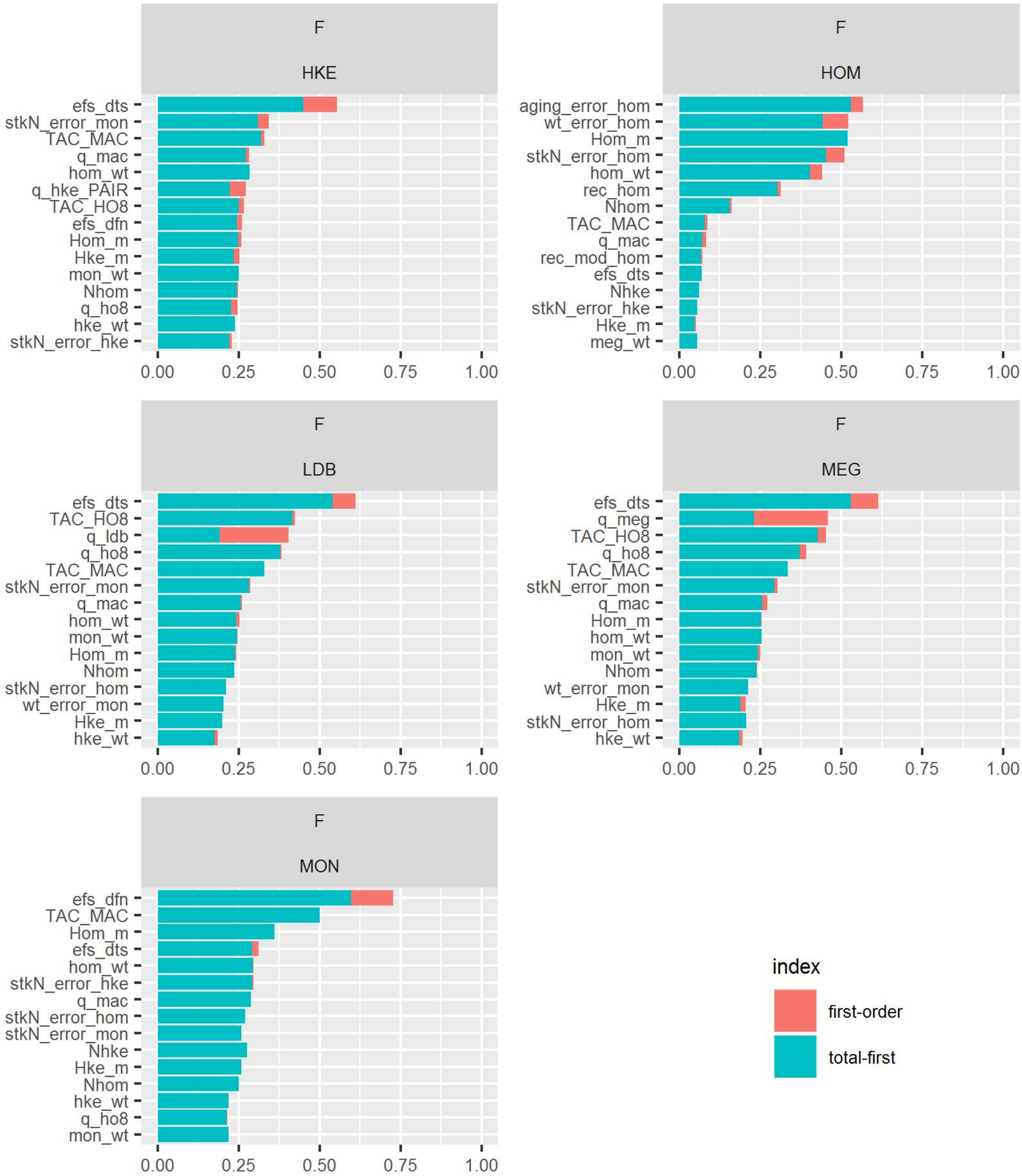

Figure 5.17: Sobol *first-order* and *total-effect* indices for **fishing mortality (F)** of all the stocks. Only the 15 factors with highest total index are shown. The red part corresponds with *first-order* index and the entire bar (blue + red) with the *total-effect*.

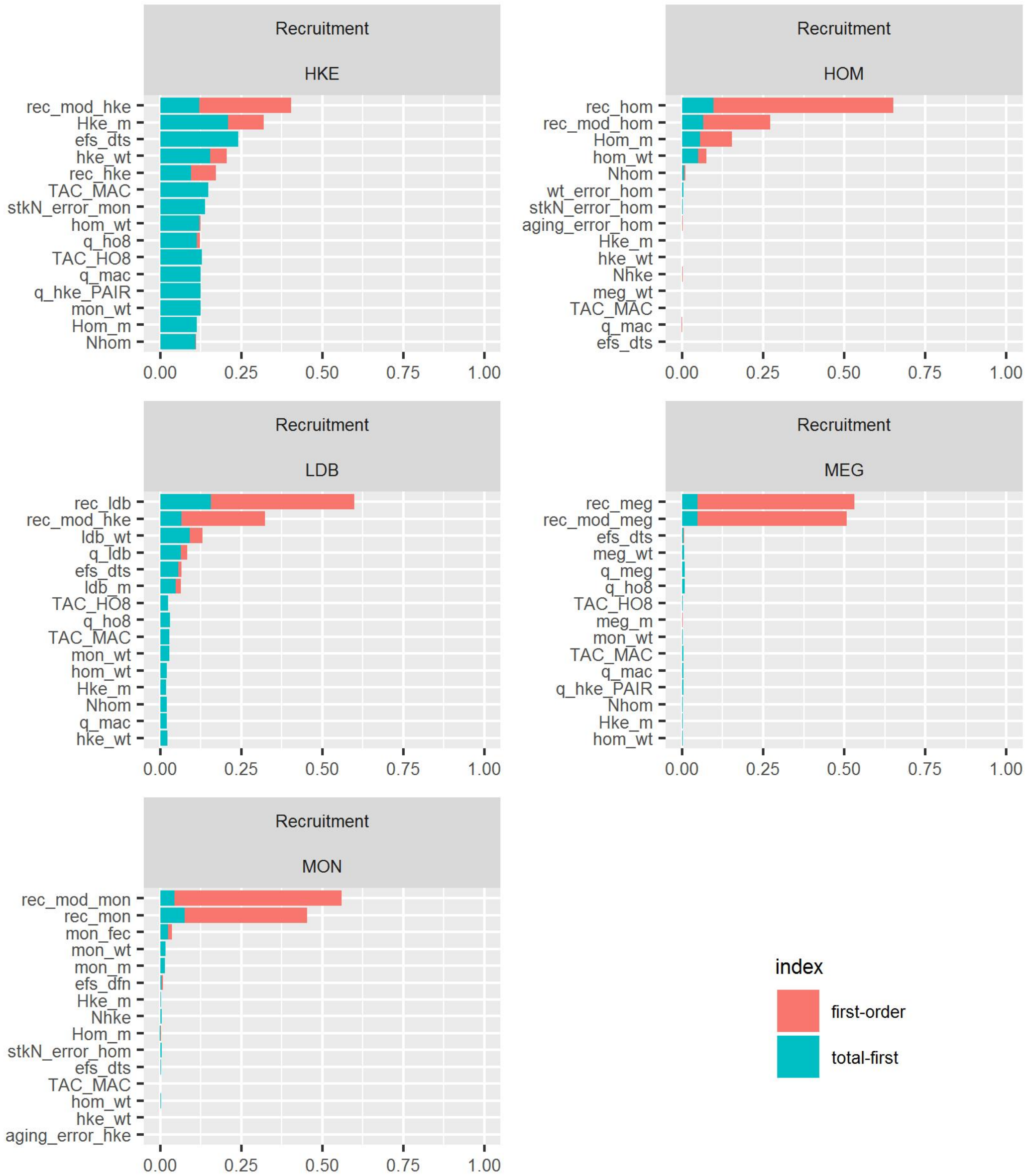

Figure 5.18: Sobol *first-order* and *total-effect* indices for **recruitment** of all the stocks. Only the 15 factors with highest total index are shown. The red part corresponds with *first-order* index and the entire bar (blue + red) with the *total-effect*.

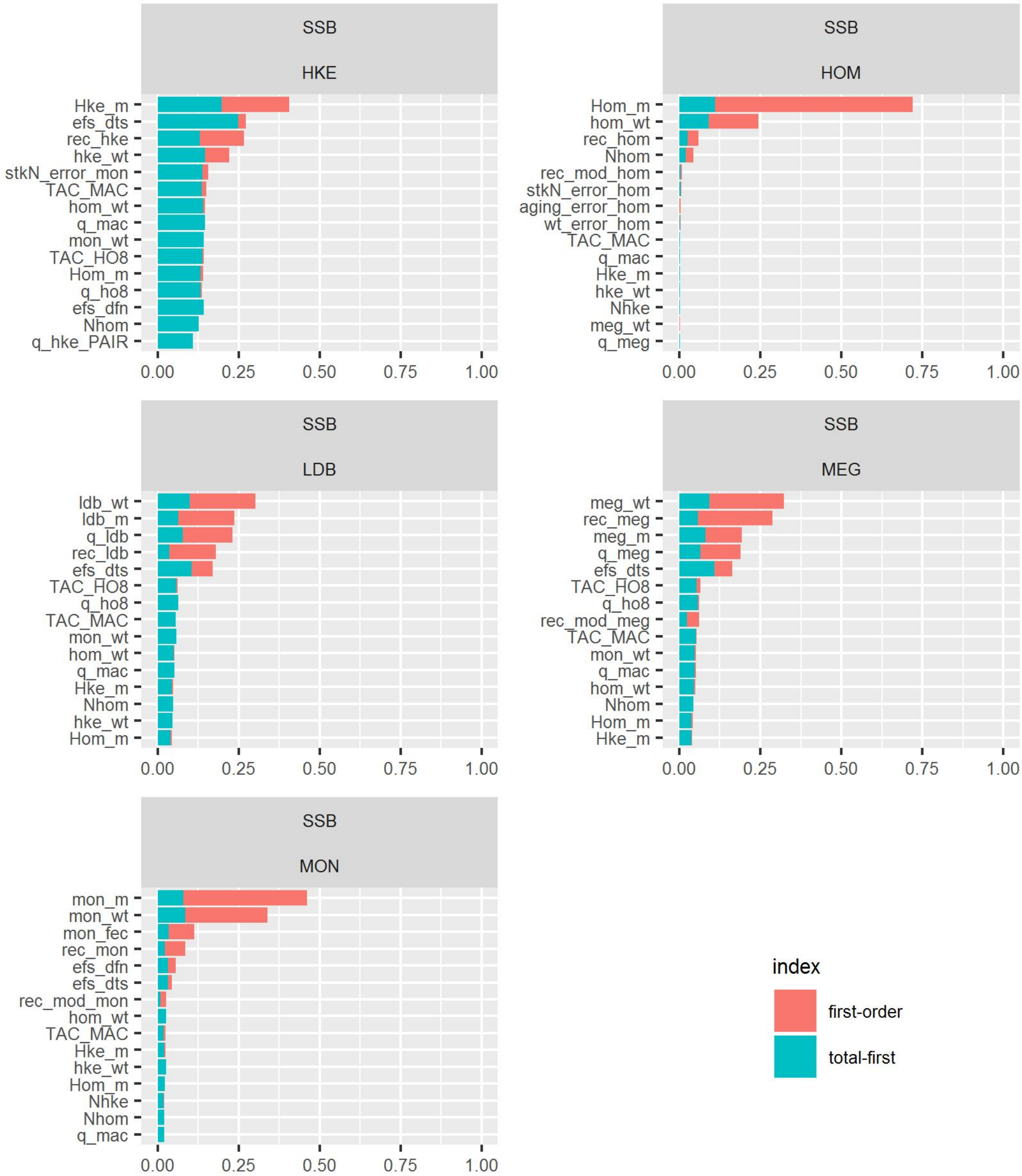

Figure 5.19: Sobol *first-order* and *total-effect* indices for the **spawning stock biomass (SSB)** of all the stocks. Only the 15 factors with highest total index are shown. The red part corresponds with *first-order* index and the entire bar (blue + red) with the *total-effect*.

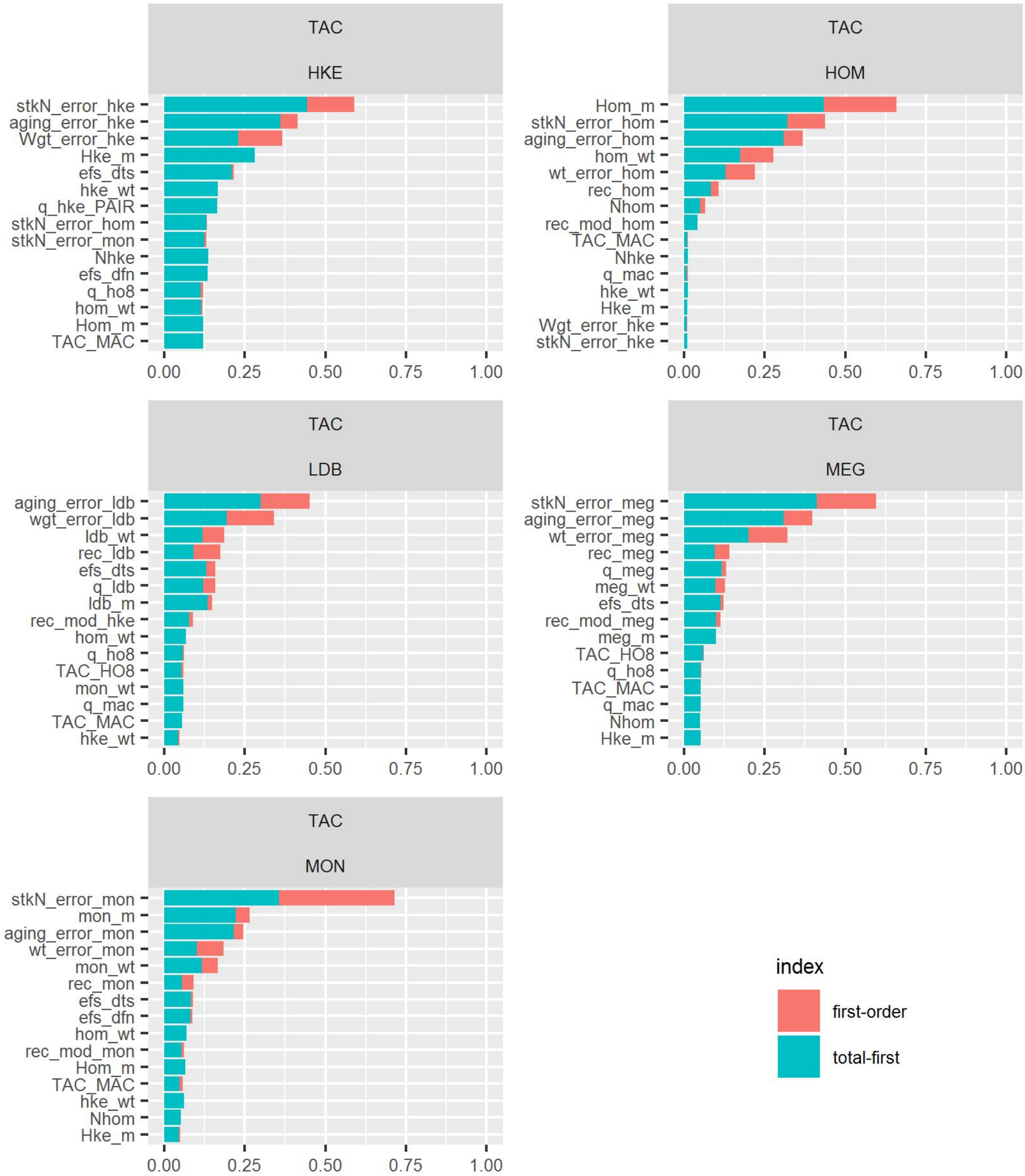

Figure 5.20: Sobol *first-order* and *total-effect* indices for **total allowable catch (TAC)** of all the stocks. Only the 15 factors with highest total index are shown. The red part corresponds with *first-order* index and the entire bar (blue + red) with the *total-effect*.

higher than 5%. In the short-term, the economic input factors were in the top ten list but in the long-term other factors gained relevance to the detriment of economic ones.

Effort, gross value added and profits (Figure 5.21 and 5.22). In the long-term, for the three fleets, the results for effort, GVA and profits were very similar . The biggest difference was observed in the ranking of economic factors which impact was higher on profits than in the other two output variables. Hence, for simplicity, here, we focus only in the results of profits. For gillnetters, the effort share was the most important factor followed by the observed error in the abundance of monkfish and hake. After these three factors the impact of the factors decreased steadily. In the top 15 list there were the natural mortality and weight of hake and horse mackerel, the weight of monkfish, the aging error in hake and monkfish, the TAC and catchability of mackerel, the effort share of trawlers and the observation error in the abundance of horse mackerel and the weight of monkfish. In the case of trawlers the effort share was in the first place and then the impact decreased steadily. Among the most important factors were the TAC and catchability of mackerel and western horse mackerel, the observation error in the abundance and weight of monkfish, the weight and natural mortality of hake, horse mackerel and monkfish and the initial abundance of hake. In the case of longliners the observation error in the abundance of hake was most important than the effort share. In this fleet the factors related with hake were predominant. In fact, the catchability of the pair metier of trawlers was also in the top 15 list. The effort share of the other two fleets, the catchability and the TAC of mackerel and the weight of horse mackerel and monkfish had also a significant impact on the profits of the longliners.

Number of vessels (Figure 5.22). The variability in the number of vessels was explained almost completely by the maximum number of days a vessel was able to work annually. In the case of gillnetters and longliners, this factor in isolation explained around 95% of the variance and for trawlers the percentage decreased up to 86%. The other factors that contributed to the variance were, the share of the income used to pay the salaries (crewshare), the maximum proportion of vessels that are allowed to exit the fishery yearly (w_1), and the effort share. The contribution of crewshare was specially relevant, a *first-order* effect around 6%, in the case of trawlers.

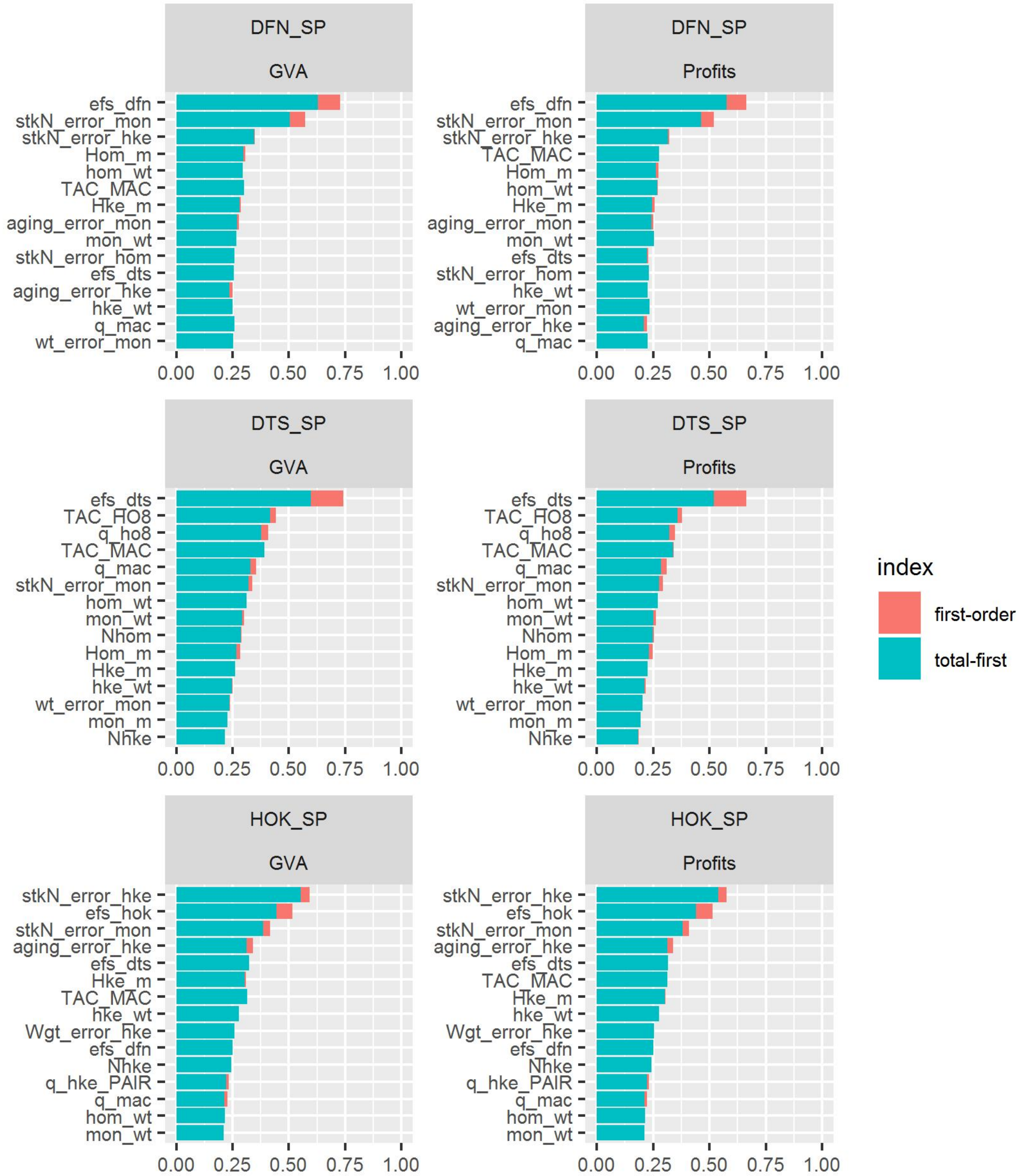

Figure 5.21: Sobol *first-order* and *total-effect* indices for **gross value added (GVA)** and **profits** at fleet level. For each fleet and output variable only the input factors with the highest total index are shown. The red part corresponds with *first-order* index and the entire bar (blue + red) with the *total-effect*.

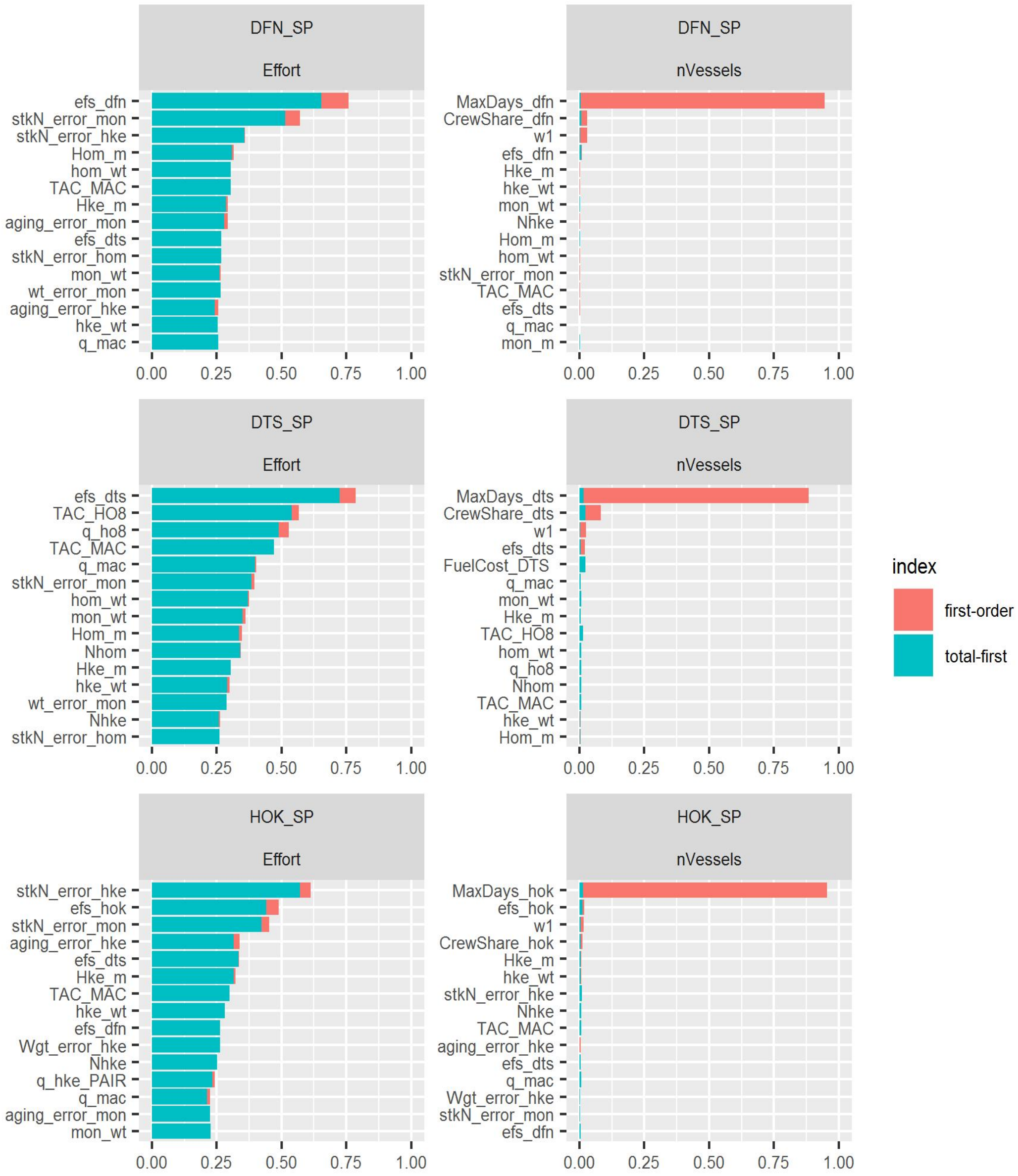

Figure 5.22: Sobol *first-order* and *total-effect* indices for **effort** and **number of vessels** (nVessels) at fleet level. For each stock and output variable only the 15 input factors with the highest total index are shown. The red part corresponds with *first-order* index and the entire bar (blue + red) with the *total-effect*.

5.3.3.4 Global indices

We used the method proposed by Lamboni et al. (2011) to calculate the *generalised* sensitivity indices using all the output variables over all the projection years. The main result obtained at single output variable level was corroborated by the global index: the output variance was largely explained by the interaction between input factors (Figure 5.23). Thirty factors were "lower sensitivity" factors (contributing less than 5% to the overall variance (Sarrazin et al. 2016)), i.e., only 26 factors had a significant contribution to the output variance. The 19% of the input factors if we take into account also those discarded by the Morris method.

The effort share of trawlers was, by far, the factor which had the highest impact on the output variables. It has a *first-order* effect of only 5% and most of the impact was in interaction with other stocks. In the second position there was the effort share of gillnetters followed closely by the natural mortality of hake and horse mackerel and the weights of these stocks and of monkfish. In a second group that covers until the 23-th factor, there were all the catchabilities, the observation errors in abundance, some biological parameters and the effort share of longliners. The observation errors in age reading and weight for hake, horse mackerel and monkfish, some biological parameters and the crew-share of gillneters. In the lower part of the table there were the maximum number of days factor, which contribution was mainly of *first-order*, all the stock-recruitment parameters, all the economic factors except the crew-share of trawlers, the maximum proportion of vessels that were allow to exit the fishery yearly (w_1) and the errors in the MP related with the two megrims.

5.4 Performance of the selection criterion

The individual and overall level performance indicators defined in Section 3.4 were calculated for $Z = 2, 3, 4$ and for the three criteria, the *calibrated visual* criterion, the *fixed number of factors* criterion and the *Savage* criterion. For $Z > 4$, the number of input factors selected with the *calibrated visual* criterion was higher than 56. Hence, it made no sense to calculate the performance indicator because all the input factors selected by the Morris method were selected by the *calibrated visual* criterion.

Furthermore, we evaluated the sensitivity of the performance of the *calibrated visual* criterion to the choice of the output variables. We took three subsets of output variables, calculate the corresponding *generalised* sensitivity indices and apply the selection criterion using the output variables selected to calculate the perfor-

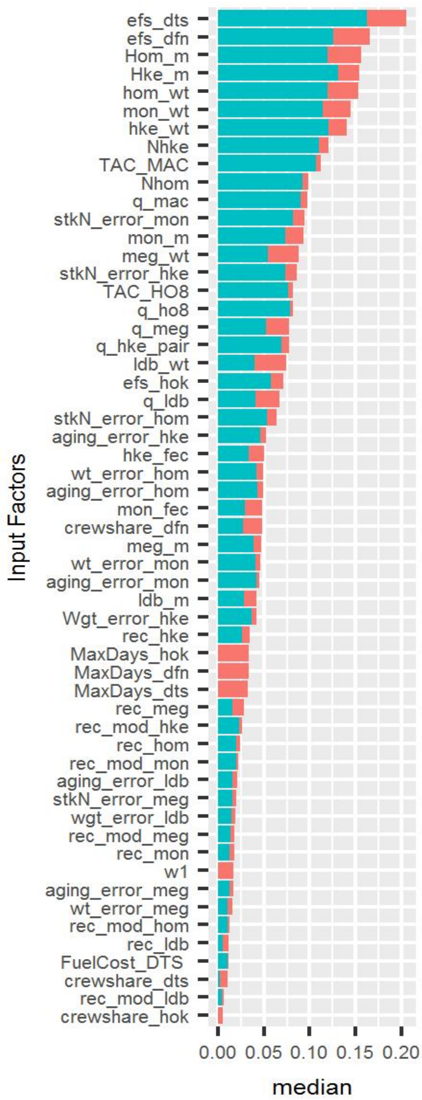

Figure 5.23: *Generalised first-order* and *total-effect* sensitivity indices. Blue bars correspond with the *first-order* sensitivity indices and the sum of the blue and red bars with the *total-effects*. Figure taken from Garcia et al. (2019a)

mance indicator. In the first set we used all the output variables, i.e., a set with 37 variables. In the second subset, we removed fishing mortality and GVA from the output variables because they were highly correlated with the rest of the variables. The resulting subset had 29 output variables. In the third subset, besides fishing mortality and GVA we also eliminated catch and effort, resulting in a subset with 21 output variables. With this selection of output variables we removed the those that were highly correlated with the rest and made the output variables which variance was explained by few input factors predominant.

The performance indicator of the *calibrated visual* criterion was always closer to one than that of *fixed number of factors* criterion (Table 5.5), i.e, the input factors selected with the *calibrated visual* criterion corresponded with input factors that were higher in the ranking of the *total-effects*. The indicator for *Savage* criterion was the indicator closest to one only for the indicator at overall level when $Z \neq 4$ (Table 5.5).

Table 5.5: The performance indicator that measures the match between the ranking obtained in the *generalised* sensitivity indices and the indices selected by the Morris method using the *calibrated visual* criterion, the *fixed number of factors* criterion and the *Savage* criterion. The first column corresponds with the number of output variables used, the second column with the number of input factors, and the rest of the columns with the value of the performance indicator defined in equation (3.9) and the generalised performance index for each of the criteria. = four spot megrim, MEG = megrim, MON = monkfish, DFN = gillnetters, DTS = trawlers and HOK = longliners). Reprinted from Garcia et al. (2019a).

Output	Input	Performance Indicator			Generalised Performance Indicator		
variables	factors	Fixed Number	Savage	Calibrated	Fixed Number	Savage	Calibrated
21	29 (Z=2)	0.56	0.52	0.64	0.47	0.68	0.56
29	31 (Z=2)	0.59	0.60	0.69	0.55	0.71	0.64
37	32 (Z=2)	0.59	0.62	0.66	0.56	0.72	0.63
21	39 (Z=3)	0.69	0.63	0.78	0.61	0.79	0.73
29	41 (Z=3)	0.70	0.72	0.81	0.67	0.82	0.77
37	44 (Z=3)	0.73	0.76	0.84	0.72	0.84	0.81
21	46 (Z=4)	0.82	0.71	0.91	0.72	0.84	0.85
29	50 (Z=4)	0.87	0.79	0.94	0.83	0.86	0.92
37	53 (Z=4)	0.86	0.81	0.96	0.83	0.87	0.94

5.5 Discussion

We conducted a GSA of `FLBEIA` bio-economic model applied to the demersal fishery around the Iberian Waters. The efficient conditioning of the model and the robust combination of Sobol (Sobol 1993) and Morris (Morris 1991) methods allowed us to carry out the analysis at a moderate computational cost. First, we identified the most important factors using the Morris elementary effects screening method. We used the selection and convergence criteria defined in Chapter 3 to avoid the subjectivity in the selection process and to ensure the convergence of the method. Then, we decomposed the output variance using the Sobol *first-order* and *total-effect* indices. Both methods were applied to the multi-dimensional output of the model. Finally, we calculated the *generalised* sensitivity indices proposed by Lamboni et al. (2011) to decompose the overall variance using only two indices per factor, the *generalised first-order* and *total-effect* indices.

5.5.1 The Morris method

The selection criterion defined in this thesis allows to select the most important factors using the same criterion for all the output variables and to use it in an automatic way, for example in bootstrap simulations. The new criterion provides a good approximation of the *visual* approach and has the advantage of being consistent along the whole selection process and of being able to be used in an automatic way. Other authors use the *fixed number of factors* criterion applied to each output variable (DeJonge et al. 2012, Hussein et al. 2011, Morris et al. 2014). This approach is consistent along output variables, but could lead to unimportant input factors being selected in some cases (for example, in recruitment) and to important ones being discarded in others (for example, in profits). Campolongo et al. (2007) used *Savage* scores (Savage 1956) to identify the most important input factors in a multi-dimensional output model. However, *Savage* scores are mostly used to compare ranking of input factors obtained using different approaches (Borgonovo et al. 2003, Confalonieri et al. 2010, Cucurachi et al. 2016) and this is the first time that their performance as a selection criterion has been evaluated.

The *calibrated visual* criterion was better than *fixed number of factors* and *Savage* criteria when comparing their performance for each output variable. Hence, if the objective is to explain the variance of every single output variable the *calibrated visual* criterion would be always preferred. For example, in the case study used here, the *Savage* criterion discarded the input factor that explains most of the variance in the number of vessels output variable. This happened because *Savage* criterion penalizes the input factors that are important in only one output variable in favor of those that are important in several variables, even if the variables are correlated. However, at overall level, if a small number of input factors were selected, the performance of the *Savage* criterion was better. This was because the basis of the *generalised* sensitivity index is more similar to the *Savage* criterion than to the *calibrated visual* one.

The comparison of the performance of the criteria was evaluated using the ranking of the *total-effects* estimated by the Sobol method, considered as the reference method by many authors (Confalonieri et al. 2010, Homma and Saltelli 1996, Sarrazin et al. 2016, Yang 2011). The input factors in the application of the Sobol method were selected by one of the criteria evaluated, the *calibrated visual* criterion. This fact may seem to produce a positive bias towards this criterion. However, the number of input factors selected by the criteria in the evaluation were lower than those considered in the Sobol method, especially for $Z < 4$. Hence, the ranking used for the performance evaluation was considered sufficiently broad to provide an unbiased assessment.

The initial abundances and the maturity were discarded for most of the stocks by the Morris method. The screening was based on the output variables in 2020 when the effect of initial abundance was already dissipated, specially for the stocks with shorter lifespan. The effect of maturity was low in the whole time series because in the older ages, the ages with the highest contribution in weight to the SSB, there was no variability (note that the individuals in old age classes are always mature, hence there was no uncetainty) and the contribution of young classes was marginal.

The Morris method discarded most of the economic factors. On the one hand, the model used to describe the effort allocation in each year was independent of economic factors. Hence, the economic performance of the fleets was primarily affected by the stock abundance and the economic factors acted only as multipliers. On the other hand, although the entry-exit of new vessels in the fishery was driven by the economic performance of the fleet, in most of the iterations there was either no variation in the number of vessels or a constant decrease limited by the parameter w_1 (the input factor that limits, in percentage, the annual decrease in number of vessels). Hence, the variability in the number of vessels was driven principally by the maximum number of days a vessel operates along the year and by w_1. As economic factors were basically multipliers, unlike the biological factors and observation errors, their impact on the short-term was higher than in the long-term.

While the observation errors in abundance were among the most important factors in the Morris method, the observation errors in landings and discards were discarded. The abundance estimates were obtained applying two errors to the real abundance, a multiplicative error and an error associated to the wrong assignation of age. However, in reality, the abundance estimate is obtained using a mathematical model which depends on yearly landings and discards. Hence, the accuracy of the abundance estimates is directly related with the quality of the data used to estimate it. Thus, it is likely that the importance of the observation errors in landings and discards was under-estimated.

5.5.2 The Sobol method

The MSE approach allows the formal incorporation of uncertainty in the decision making process (Punt et al. 2016). However, a proper uncertainty conditioning is not always carried out to condition the models. Uncertainty in recruitment process is one of the uncertainties most commonly used in fisheries management simulation models (Kraak et al. 2010). In fact, in the evaluation of multiannual management plans and the subsequent application presented in Chapter 4 only stock-recruitment parameters were considered uncertain (Garcia et al. 2017a, STECF 2015a). The GSA carried out in this chapter showed that recruitment was the most important factor only in the recruitment variable itself. In the SSB the variability around recruitment curve had also a significant impact. However, for the rest of the output variables its contribution to their variance was marginal. In fact, in the *generalised* sensitivity index the factors related with recruitment appear in the lower part of the ranking (Figure 5.23). Similar behaviour was observed by Gasche et al. (2013). On the contrary, the parameters of the stock-recruitment of one of the stocks in Drouineau et al. (2006) was among the most important factors. In this case, the use of a linear model to simulate the recruitment made it more influential on the results. A complete uncertainty conditioning is usually difficult to carry out due to the effort needed to condition all the input factors. With the application of the Morris and Sobol methods we found that only 19 input factors, i.e the 14% of the total input factors, had significant impact on the output variance. Carrying a a proper uncertainty conditioning of only those 19 input factor would be approachable task.

The first thing that drawed attention in the Sobol variance decomposition method was the prevalence of the *total-effects*. In the first year of simulation the variance was explained mainly by *first-order* effects but their importance decreased with years. Most of the processes in the model are interlinked through the stock abundance, and therefore, the emergence of interactions was somewhat expected. The importance of interactions was specially marked in those output variables related with the effort of the fleets, that is, the catch, the effort itself, the fishing mortality, the

GVA and the profits. Fleets' effort depended on the stocks' TAC, catchability, and biomass. In turn, the TAC depended on the errors in the management procedure, and the abundance on the recruitment and biological parameters. That is, although not directly, the effort was closely related to many of the factors of the system, so that *total-effect* indices were significant for many of them. Because of this interdependence, most of the factors contributed to the variance of many output variables (Figure 5.14). The same behaviour was observed by Gasche et al. (2013) where fishing mortality was the output variable most affected by interactions between factors. However, unlike here, in that analysis the interactions did not drive the variability. Their effort allocation model could depend on less factors than our model or have less technical interactions between stocks which could produce that the variability of fishing mortality and catch variables are less affected by interactions.

Effort share, the key factor in the simulation of fleets' short-term dynamics, was among the most important factor in many of the output variables. Furthermore, the effort share of trawlers and longliners were the two most important factors in the *generalised* sensitivity indices. Fleets' short-term dynamics is one of the main components in bio-economic simulation models and there exists different approaches to simulate them (see for example Marchal et al. (2013), Salas and Gaertner (2004), van Putten et al. (2012) or Girardin et al. (2016)). However, the parameters of the models used are often maintained fixed along the simulation (Andersen et al. 2010, Bartelings et al. 2015, Bellanger et al. 2018, Garcia et al. 2017a, Simons et al. 2015). Gasche et al. (2013) used a short-term dynamics model which mixed tradition and economic expectation to predict the effort allocation. Using GSA they found that some of the input factors of the short-term dynamics model were among the most important factors. However, the relative importance was lower than the importance of effort share in the present implementation, predictably because they did not consider any economic variable to summarize the results. In three years of data available, the CV varied from 5% to 112%. A longer time series should be necessary to conduct an adequate uncertainty conditioning.

Natural mortality was among the most important factors. However, the knowledge about natural mortality is generally very poor (Legault and Palmer 2016). Moreover, in many MSE applications it is considered deterministic and equal to the value used in the assessment model of the stock (Garcia et al. 2017a, Kell et al. 2006b, Marchal and Vermard 2013, Simons et al. 2014). In turn, stock assessment model implementations often assume it constant along years and ages (Johnson et al. 2015). Here we mimicked the MP used in reality for the stocks, i.e, natural mortality was equal to the value used in their assessment model independently of the value used in the OM. However, this way of simulating the system did not allow us to quantify explicitly the contribution of the observation error in natural mortality on the output variance. The contribution of this error was implicit in the contribution of the natural mortality itself. If we wanted to quantify the impact of increasing the knowledge about natural mortality we should include an error factor in the MP that increases the accuracy of the value used in the MP in relation to the value in the OM.

For all the stocks but hake, the variability in recruitment, SSB and TAC was explained by a small set of factors. The mean recruitment of the non-hake stocks was constant for biomasses bigger than a reference level and the probability of falling below it was very low in the simulation. Hence, the recruitment of these stocks was driven mainly by the variability in the factors related with the recruitment itself. The variability in SSB was mainly driven by weight and natural mortality and the impact of maturity was residual, as explained above. However, using SSB as a proxy for reproductive potential may not be adequate (Murua et al. 2010) and the factors associated to alternative proxies, like egg production by age, could be more sensitive.

The sensitivity indices obtained for effort, GVA and profits were similar, the ranking of factors was almost the same and also their value. The profits and GVA are considered in the simulation as a translation of effort into monetary terms using economic factors and the catch production. Many of the economic factors were discarded by the screening method and in the variance decomposition approach they were fixed to their mean value. Hence, the uncertain factors in the variance decomposition method had similar roll in the calculation of sensitivity indices for effort, profits and GVA and their value was similar.

The variability of the TAC for all the stocks was explained in a great extend by the observation errors, i.e, the epistemic uncertainty. It would be expected that these factors had similar importance in catch, but this happened only for hake and horse mackerel. These two stocks were the main target stocks of the fleets and the effort was driven by their catch advice. Hence, the actual catch of the other stocks was almost independent of their TAC and the fishery could be managed through the management of hake and horse mackerel. This is a relevant finding for fisheries management. At present, a lot of research is being carried out to manage the so called data-limited stocks (Carruthers and Hordyk 2018, Jardim et al. 2014a, Kokkalis et al. 2017), the stocks for which the lack of reliable data prevents the quantitative assessment of the stocks. If results from GSA could be used to conclude that the assessment for some stocks is not necessary it would save a lot of time to fisheries scientist and therefore a lot of money to society. However, the lack of a quantitative assessment should not preclude having a catch limit because not having it could create incentives to over-exploit the stock.

From the management point of view, one of the potential uses of GSA is to identify the most efficient way of reducing variability to improve the decision making process. The epistemic uncertainty, the uncertainty that could be reduced with further research, corresponds solely with the observation errors in the MP (see the table in Appendix B.1). The sum of the variability associated to these factors indicate how much the variability could be reduced if the management process was improved through data collection, improvement of stock assessment accuracy or further research for example to estimate natural mortality. TAC for all the stocks and economic output variables for trawler fleet were the only variables that could be directly benefited from a decrease in epistemic uncertainty. If the uncertainty in the observation errors could be removed completely the uncertainty in those output variables would decrease in at least a 30% (Figure 5.15). This amount corresponds with the uncertainty produced by the input factors in isolation, hence it would increase with the variability associated with the interaction between observation errors and other factors.

The patterns in the sensitivity indices of hake and horse mackerel differentiated from those of the other three stocks. In the case of hake there were two main reasons, first, the recruitment was simulated with a ricker model, and sencond, it was the target stock of most of the fleet/metiers. The ricker stock-recruitment model (Ricker 1954), unlike the model used for the rest of the stocks, is sensitive to changes in SSB in the whole domain of existence, hence all the factors with an impact on SSB had also an impact on recruitment. Moreover, hake was caught in most of the metiers and had a big technical interaction with the rest of the stocks. Thus, most of them had at least a small contribution to the variance of hake's output variables when interacting with other factors. In the opposite side was horse mackerel. Most of the catch of horse mackerel (around 60%) was generated by two fleets that catch only this stock (these fleets were not included in the economic analysis because they were not part of the Spanish demersal fishery). Hence, horse mackerel's output variables were explained by a few number of input factors and the variance explained by interaction between input factors was low. Another remarkable pattern at stock level was the similarity between the importance indices of both megrims. These two stocks are caught in the same metiers so are subject to the same technical interactions. Hence, the impact of factors not directly related with the two stocks themselves was the same.

As happened at stock level, at fleet level, the dynamic of the fleets also marked the contribution of the factors to the variance. Trawlers catch all the stocks without a clear target, hence the variance of its output variables was explained by a big number of input factors. On the contrary, as longliners target hake and the catch of the other stocks is less important, the variance of its output variables was primarily explained by the variance in the hake input factors.

5.5.3 The conditioning

Although uncertainty should be conditioned according to the existing data, usually the limited data available do not allow an adequate uncertainty conditioning. An approach frequently used in GSA is to introduce uniform distributions centred in the mean of the observed values with a CV of 20% (Lehuta et al. 2010). Gasche et al. (2013) used a CV of 50% and oppositely Morris et al. (2014) considered that a CV of 10% was sufficient to encompass the existing uncertainty. We evaluated the robustness of using a CV of 30% by comparing the results of the Morris method with those obtained using a CV of10% and 50% and found that the input factors selected in both cases were similar. The intervals should be sufficiently wide to represent the inherent uncertainty and sufficiently narrow to obtain rational results (Leamer 1985). But, the larger the input domain, the greater the number of iterations needed to achieve convergence. Hence, a compromise is needed between the size of the input domain and the computational cost of the GSA implementation. The results of this analysis should be used to guide the uncertainty conditioning of future implementations of `FLBEIA` in this case study. As mentioned previously, the analysis should be only focus on 19 input factors.

The efficient conditioning of the model lead to a big reduction in the number of effective input factors of the model. This resulted in the exact same reduction in the computational cost of the analysis. Applying the Sobol method with the original number of input factors would have been unfeasible without a system with an enormous computational power. When the number of effective factors is reduced, information is lost. In the case of groups, the effect of individual factors is hidden by that of the group. Hence, the groups should be as homogeneous as possible in relation to the impact of the individual factors in the output variables. Alternatively, Sheikholeslami et al. (2019) proposed a methodology to identify the groups based on the convergence and stability properties of the Sobol method. The group formed with this method ignore completely the nature of the elements that form it. In turn, in the quantile transformation approach all the values in the vector are moved in the same direction and with the same intensity. Therefore, the individual values' variability is ignored. Hence, to avoid a misrepresentation of the variability when this approach is used, the individual values' variance should be negligible in comparison with that of the vector as a whole.

Weight is routinely sampled for commercially important stocks and the CV associated to weight at length would be less than 30%. However, here we considered weight at age which implicitly took account of growth in length of fishes. Furthermore, growth in length is not easy to estimate due to the difficulty in validating an aging method. Hence, a CV of 30% in weight at age, which includes variability in growth and in weight at length, did not seem unreasonable.

In the application presented, we mimicked a typical European management procedure (Salomon et al. 2014); however, the uncertainty conditioning should be adjusted to the reality of the fishery system and the study's objective. As the MSE simulation models differentiate clearly epistemic and natural uncertainty, GSA can be used to perform a cost-benefit analysis of increasing the sampling intensity or of improving the assessment models. Therefore, the conditioning of the variables in the management procedure should be adapted to the study's objective.

5.5.4 Implementation of the methods

We applied the convergence criteria defined in chapter 3 with a value of ν equal to 95%, but other values could also be adequate. Higher values of ν could slow down the convergence and lower ones could lead to the selection of unimportant factors. We recommend using high values of ν, as long as computational resources allow it. We could have assessed the convergence using the *input factor screening* criterion in Sarrazin et al. (2016). This criterion focuses on the width of the confidence intervals of the non-selected factors (factors X_k for which $m^r_{X_k} < 0.95 \cdot N_{boot}$) and considers that it has converged when the width is narrower than 0.05. Of the 79 factors with $m^r_{X_k} < 0.95 \cdot N_{boot}$, only 26, i.e., 33%, had converged when $r = 300$. Therefore, according to this criterion we should increase r with the subsequent increase in computational cost.

We used a base sample of $N = 10000$ iterations. However, for few combinations of output variables and input factors, ($< 5\%$) the width of the confidence interval was still bigger than 0.05 (Figure 5.12). Even so, we are confident that increasing the size of the base sample will not alter the conclusions because the general picture obtained with 2000 iterations did not change increasing the base sample size.

The extended FAST method (Saltelli and Bolado 1998) and metamodels (see Saltelli et al. (2008) for a brief introduction to metamodels and relevant references) are quicker GSA alternatives to the Sobol method (Pianosi et al. 2016). However, FAST is biased and unstable when the number of input factors increases (Iooss 2015) and the Sobol method is considered the reference by many authors (Confalonieri et al. 2010, Homma and Saltelli 1996, Sarrazin et al. 2016, Yang 2011). Using emulators implies to fit an statistical model to a big enough realizations of the original model and to calculate the importance indices using the emulator. Finding a model that provides an adequate fit would require a big personal effort and the save in computational time might not be worth it.

The ranking obtained with the *generalised* sensitivity index depends on the output variables used to summarize the results. In this case for example, as the *generalised* index removed correlation and effort, GVA and profit variables were correlated, the weight of economic input factors was lower than that of biological ones that were influential in less correlate output variables such as SSB and recruitment.

As the output variance was driven by the interaction between factors, a deeper research would involve to identify the specific components of those interactions. Saltelli (2002) proposed a method to compute the importance indices for the interactions of order $K-2$ using the same model outputs used to compute the *first-order* and *total-effects* indices. Nevertheless, for $K = 56$, the indices corresponding to $K-2$ order interactions would not shed much light on the problem. He also proposed a method to calculate the indices of order 2 at a cost of $2N(K+1)$ model evaluations, i.e., almost double the actual cost. However, as many factors have a large *total-effect* index, the interactions would probably involve more than two factors and the extra computational cost would not be worthwhile.

In summary, the efficient conditioning of the model together with the application of the Morris method allowed to decrease the number of the input factors in 96%. The reduction in the number of input factors was directly translated in the same reduction in the computational cost of the GSA. Moreover, the conditioning removed the correlation between the input factors which allowed to apply standard GSA methods. From the point of view of the application of the methodology, the variance decomposition method provided a deep understanding of the internal behaviour of the model. Moreover, we found that the combination of GSA and the MSE approach could be used to identify the stocks for which it is necessary to have an accurate stock assessment model to guarantee an adequate management of the fishery system.

Chapter 6

Software

6.1 Introduction

`FLBEIA` model described in Chapter 2 was implemented in R (R Core Team 2019) and it is distributed as an R package. Furthermore, a second package `FLBEIAShiny` was developed to provide an easy and interactive way to analyse the simulation results obtained with `FLBEIA`. The selection and convergence criteria defined in Chapter 3 were also implemented in `R` to facilitate their use. In addition, the whole set of plots of the AEEs and sensitivity indices calculated in Chapter 5 were made available in a Shiny application. In this chapter we present the two packages and the Shiny application with the GSA results.

First, in Section 6.2 `FLBEIA` package is described, how to install it in `R` , the input data needed to run it and the functions available to facilitate the conditioning of the model and the analysis of the results. In the same section, the main function of the package is described in detail and several examples are given on how to run the model. Then, in Section 6.3 the `FLBEIAShiny` library is presented, how to launch the Shiny application, the input data needed and the contents. A practical example on how to use the `R` functions that implement the selection and convergence criteria are described in Section 6.4. Finally, in Section 6.5 the Shiny application developed to store all the sensitivity indicators obtained in the application of the GSA is described, how to access it and the plots available.

6.2 FLBEIA

`FLBEIA` model is distributed as a R package and is available in GitHub. `FLBEIA` is part of the FLR collaborative project and the `FLBEIA` Github repository is embedded in FLR Github repository too. `FLBEIA` depends on some of the FLR packages (FLCore and FLFleet) and other are used in specific situations (FLash and FLa4a for example). The source code can be directly downloaded from the GitHub webpage https://github.com/flr/FLBEIA. The compiled packaged can be downloaded from the `FLBEIA` site in AZTI's webpage (http://flbeia.azti.es). Within an R session the compiled package can be downloaded from FLR webpage directly typing the following command :

```
install.packages(repos="http://flr-project.org/R", pkgs = "FLBEIA")
```

The development version of the package can be installed from GitHub within a R session. For doing so, it is necessary to install `Rtools` software available in https://cran.r-project.org/bin/windows/Rtools/ and the R package '`devtools`'. Then, within the R session the following two commands need to be executed:

```
library(devtools)
install.github("FLR\FLBEIA")
```

Note that to install `FLBEIA` it is mandatory to install `FLCore` and `FLFleet` packages previously. The options to install these packages are the same as for `FLBEIA`.

The model was build up modularly; it was divided in small processes and one or more functions were implemented to describe each of the processes. Then these functions were assembled by functions at higher level. The functions at lower level are not available to the user. Only the function `FLBEIA`, that represents the whole model, the functions used to facilitate the conditioning of the model and the analysis of the results, and the functions used to describe HCRs are available to the user. The HCRs belong to an individual process and they should not be available to the user. However, it could be useful to apply them outside `FLBEIA`. Hence, it was decided to made them available to the final user.

Each of the public functions has its own help page explaining what the function does, the arguments (input objects) needed to use them and the shape of the output. Furthermore, in some cases there are practical examples of the application of the functions.

6.2.1 New classes

The FLR libraries were developed using object oriented programming and make use of S4 classess in R (Chambers 1998). In `FLCore` and `FLFleet` packages specific S4 classes (special classes defined in R for object oriented programming) were defined to store the most common data used to model fishery systems. `FLBEIA` uses those classes to store and operate with the data but it also defines new classes. The terms listed below correspond with the name of the new classes defined in `FLBEIA` and with the methods to construct them.

`FLBDsim` stores the data and parameters needed to project biomass dynamics populations.

`FLCatchExt` stores the data relative to the catch of each stock at fleet-metier level.

`FLCatchesExt` stores the catch data of all the stocks caught at fleet-metier level. It is a list of `FLCatchExt` objects.

`FLFleetExt` stores catch, economic and technical data relative to the activity of the fleet at fleet, metier and stock level. It is formed by an element of class '`FLMetiersExt`', some descriptive elements of class `character` and some elements with fleet level data of class '`FLQuant`'. The class '`FLQuant`' is the basis class defined in `FLCore` to store quantitative information.

`FLFleetsExt` is used to store economic, technical and catch data of all the fleets in the fishery system. It is a list of '`FLFleetExt`' objects.

`FLMetierExt` stores economic, technical and catch data relative to the activity of the fleet at metier and stock level. It is formed by an element of class '`FLCatchesExt`' and some additional elements of `character` and `FLQuant` class.

`FLMetiersExt` stores economic, technical and catch data of all the metiers within a fleet. It is a list of '`FLMetierExt`' objects.

`FLSRsim` stores the data and parameters needed to simulate the recruitment in age structured populations.

6.2.2 Functions to generate `FLBEIA` input data

`FLBEIA` package provides a set of functions to facilitate the generation of the input data and arguments needed to run the model. There are two types of input arguments in the call to `FLBEIA`; the data objects and the control objects. The data objects are used to store the data and the control objects to specify the model settings. The control objects are used to declare the models that will be used to describe the processes and the parameters of these models. There are functions to generate both, the data objects and the control objects. There are two type of functions available to generate the data objects which differentiate on the shape of the input data they use, data frames or arrays. The tutorial `http://www.flr-project.org/doc/Conditioning_FLBEIA.html` explains in detail how to condition `FLBEIA` using these functions. The `FLBEIA` call has the following arguments:

```
biols, SRs, BDs, fleets, covars, indices, advice,
main.ctrl, biols.ctrl, fleets.ctrl, covars.ctrl,
obs.ctrl, assess.ctrl, advice.ctrl
```

A description of each of the arguments is given in section 6.2.6 and they can be created using the functions listed below.

- `create.advice.data, create.assess.ctrl, create.BDs.data, create.biols.data, create.fleets.data, create.indices.data, create.SRs.data:` Creates the advice, BDs, biols, fleets, indices and SRs arguments respectively necessary to run `FLBEIA` using data frames stored in files of 'cvs' format.
- `create.biol.arrays, create.fleets.arrays:` The first function creates the `FLBiols` object necessary to run `FLBEIA` using input data stored in R arrays or in excel files. The second one creates the `FLFleets` object necessary to run `FLBEIA` using input data stored in Intercatch like data format `http://www.ices.dk/marine-data/data-portals/Pages/InterCatch.aspx`).
- `create.advice.ctrl, create.biols.ctrl,create.fleets.ctrl, create.obs.ctrl:` Create the control objects necessary to inform `FLBEIA` about the models and parameters needed to simulate advice, stocks dynamics, fleets dynamics and generation of observed data.

6.2.3 Functions to analyse the results

The FLR objects used to simulate the fishery system in `FLBEIA` are suitable for programming but they are incompatible with the functions and plots available in R to carry out exploratory data analysis. Most of these functions are based on data frames. There are several functions that ease the analysis of the results of `FLBEIA`. They summarize the results using a set of output variables and they store then in data frames or plot them directly. The output variables are calculated at stock, metier or fleet level and some of them are available at different levels, for example catch can be obtained at stock, fleet or metier level depending on the function used. The available output variables are:

`biomass`: total biomass, it can be obtained through `bioSum` function.

`catch`: total catch at stock, fleet and metier level, it can be obtained through `bioSum`, `fltStkSum` and `mtStkSum` functions.

`capacity`: the maximum effort that the fleet can execute in each time step, it can be obtained through `fltSum`.

`catch.iyv, disc.iyv, land.iyv`: interannual variability in catch, discards and landings, they can be obtained through `bioSum` function.

`effort`: effort exerted by the fleets in each time step, it can be obtained through `fltSum` function.

`effshare`: the proportion of total effort exerted by the fleet in each metier in each time step, it is available in `mtSum` function.

`discRat`: the discard rate, the ratio between total discards and total catch, it can be obtained through `advSum`, `fltStkSum` and `mtStkSum` functions.

`discards`: total discards in weight, it can be obtained through `bioSum`, `fltStkSum` and `mtStkSum` functions.

`fcosts, vcosts, costs`: fixed costs at fleet level, variable costs at fleet or metier level and total costs at fleet level. It can be obtained through `fltSum` function and `vcost` also through `mtSum` function. Fixed cost are obtained multiplying `fcost` and capacity slots and `vcost` multiplying `vcost` and effort slots. At metier level the effort to compute variable cost is calculated using effort share.

`f`: instantaneous reference fishing mortality rate per stock. It is obtained using the Baranov catch equation to calculate fishing mortality at age and calculating the mean over the reference age range. It is obtained through `bioSum` function.

`fep`: full equity profit economic indicator at fleet level. It is calculated as the difference between `grossSurplus` and the product between `Depreciation` and `NumbVessels`. It is obtained through `fltSum` function.

`grossValue`: the monetary value of all the landings of a fleet, i.e. the sum product of landings in weight and price. It is obtained trough `fltSum` function.

`grossSurplus`: the difference between the `grossValue` and the sum of fixed and variable cost. It is obtained trough `fltSum` function.

`gva`: the sum of `grossSurplus` and the `salaries`. It is an indicator of the goods that the fishing activity reports to the society. It is obtained through `fltSum` function.

`landings`: total landings in weight at stock, fleet or metier level. It is obtained through `bioSum`, `fltStkSum` and `mtStkSum` functions.

`npv`: net present value. It is calculated applying a discount rate to the annual `grossSurplus` over a period of time and adding them. It is obtained through `npv` function.

`nVessels`: the number of vessels by fleet, it is obtained through `fltSum` function.

`pBlim`: the probability of SSB falling below `Blim` reference point. It is obtained through `riskSums` function.

`pBpa`: the probability of SSB falling below `Bpa` reference point. It is obtained through `riskSums` function.

`pPrflim`: the probability of `grossSurplus` falling below a pre-specified reference point. It is obtained through `riskSums` function.

`price`: the price of the stocks at fleet or metier level. It is obtained through `fltStkSum` and `mtStkSum` functions.

`profitability`: the ratio between `grossSurplus` and `grossValue`, it is obtained through `fltSum` function.

`quota`: the part of the TAC assigned to each fleet. It is obtained through `fltStkSum` function.

`quotaUpt`: the ratio between the catch and the quota share by fleet. It is obtained through `advSum`, `fltSum` and `fltStkSum` functions.

`rec`: the recruitment, it is obtained through `bioSum` function.

`salaries`: the salaries, they are formed by two components, a fixed component and a variable one being the last one equal to a percentage of the gross value. It is obtained through `fltSum` function.

`ssb`: the spawning stock biomass, calculated as the sum-product of the abundance at age, weight and maturity. It is obtained through `bioSum` function.

`tac`: the total allowable catch (TAC). It is obtained through advSum function.

`tacshare`: the proportion of the TAC that belongs to each fleet, it is obtained through `fltSum` function).

The available functions to calculate and plot these output variables are listed below:

- `F_flbeia`, `SSB_flbeia`, `B_flbeia`, `R_flbeia`, `C_flbeia`, `L_flbeia`, `D_flbeia`: calculate the fishing mortality, SSB, biomass, recruitment, catch, landings or discards for all the stocks from the output of a call to `FLBEIA` function. The ouput is an array with four dimensions, one for the stocks, the second one for years, the third for seasons and the last one for iterations.
- `annexIVHCR, ghlHCR, little2011HCR, pidHCR, pidHCRItarg, aneHCRE,`

annualTAC, CFPMSYHCR, F2CatchHCR, FroeseHCR, IcesHCR, MAPHCR, neaMAC_ltmp: these functions corresponds with the HCRs described in Table 2.1 in Chapter 2. The first five correspond with model-free harvest control rules and the rest are model-based.

- bioSum, fltSum, fltStkSum, mtSum, mtStkSum, riskSum: calculate the biological, technical and economic output variables listed previously. The output are data frames with the values of the variables by stock and/or fleet, year, season and iteration.
- bioSumQ, fltSumQ, fltStkSumQ, mtSumQ, mtStkSumQ: calculates the quantiles of the biological, technical and economic output variables. The input is the output of the functions in the previous point.
- plotEco, plotFLBiols, plotFLFleets, plotbioSum, plotfltSum, plotfltStkSum: these functions generate the plot of the economic, biological and technical output variables listed above. The first three functions operate directly in the output of FLBEIA function and the rest in the output of bioSum, fltSum and fltStkSum functions.
- revenue_flbeia, costs_flbeia], totvcost_flbeia, totfcost_flbeia, price_flbeia: calculate the revenue (gross value), total costs, variable costs, fixed costs and price from an FLFleetxExt object.

6.2.4 Auxiliary functions

There are several functions that are useful from the programming and data analysis point of view and have been made available in FLBEIA package.

- stock.fleetInfo: identifies the stocks caught by each of the metiers of a certain fleet. It operates in a FLFleetExt object.
- tlandStock, tdiscStock: compute total landings or discards, in weight, from a FLFleetsExt object.
- catchStock.f, discStock.f, landStock.f: compute total catch, discards and landings at age, in numbers, from a FLFleetExt object.
- catchWStock.f, discWStock.f, landWStock.f: compute total catch, discards and landings at age, in weight, from a FLFleetExt object.
- catchStock, discStock, landStock: compute total catch, discards or landings at age from a FLFleetsExt object.
- catchWStock, discWStock, landWStock: compute total catch, discards or landings at age, in weight, from a FLFleetsExt object.

6.2.5 Datasets within FLBEIA package

The objective of having datasets is twofold, first to illustrate the use of the model to the new users and second to have a dataset against which new developments can be easily tested. The two datasets provide two contrasting examples to illustrate and test the functioning of FLBEIA. Each of the datasets contains all the necessary data to run FLBEIA and both are used in the examples provide in the FLBEIA R-help page.

6.2.5.1 one and oneIt dataset

The one and oneIt data sets provide an example of the simplest case study that can be simulated with FLBEIA, a single age structured stock and a single fleet with a single metier. The difference between both sets is that the 'one' data set only has one iteration and the 'oneIt' has three. The objects available in these datasets are:

oneAdv, oneItAdv: a list with two elements "TAC" and "quota.share". The TAC is used to store the yearly catch advice and the "quota.share" is used to store the proportion of the TAC that belong to each fleet yearly, in this case there is only one fleet so the "quota.share" is just an FLQuant filled with ones.

oneAdvC, oneItAdvC: a list used to control how the advice is generated, the HCR used, the reference points and other settings needed in the MP.

oneAssC, oneItAssC: a list used to store the settings to apply the stock assessment models. In this case no assessment is used.

oneBio, oneItBio: a FLBiols object, with only one element, with the biological data of the stock.

oneBioC, oneItBioC: a list used to store the settings to simulate the stock dynamics.

oneCv, oneItCv: a FLQuants object used to store the values of the covariates. In this case, it is used to store the economic variables that are not included in the FLFleets objects.

oneCvC, oneItCvC: a list where the models used to simulate the covariates and additional parameters needed to feed those models are stored. In this particular case all the covariates are constant along time and the 'fixedCovar' model is used for all of them.

oneFl, oneItFl: a FLFleets object, with one element, used to store fleet's technical and economic data at fleet, metier and stock level.

oneFlC, oneItFlC: a list used to control the fleet dynamics models, the models used to simulate the short-term dynamics, the catch production, the price formation, the capital dynamics and additional parameters needed to apply those models.

`oneIndAge, oneItIndAge:` a list of age-structured `FLIndices` object used to store abundance indices of the stocks, each `FLIndices` belong to one stock.

`oneIndBio, oneItIndBio:` a list of biomass `FLIndices` object used to store abundance indices of the stocks, each `FLIndices` belong to one stock. In this case there is only one element.

`oneMainC, oneItMainC:` a `list` used to control the main function `FLBEIA`. It has two elements one with the time frame of the simulation and a second one with the type of management used (simultaneous for all the stocks or independent).

`oneObsC, oneItObsC:` a `list` used to control the generation of the observed data which includes the generation of the abundance indices and the observation of the stock data. In this case the stock is observed without error and even the numbers and exploitation at age are observed perfectly. No abundance index is observed in this case.

`oneObsCIndAge, oneItObsCIndAge:` the same as `oneObsC` with an additional element to generate an age structured abundance index.

`oneObsCIndBio, oneItObsCIndBio:` the same as `oneObsC` with an additional element to generate an biomass abundance index.

`oneSR, oneItSR:` a list with one `FLSRsim` object. This object stores the model and parameters needed to simulate the recruitment and also the yearly error around the stock recruitment curve.

6.2.5.2 `multi` dataset

The `multi` data set provides an example of a complex case study with four seasons, two stocks and two fleets, both fleets with two metiers. One of the stocks is age structured and the other one is aggregated in biomass.

The objects available in this dataset are:

`multiAdv:` a `list` with two elements "TAC" and "quota.share". The TAC is used to store the yearly catch advice and the "quota.share" is used to store the proportions of the TAC that belong to each fleet yearly.

`multiAdvC:` a `list` used to control how the advice is generated, the HCR used, the reference points and additional parameters neede to apply the HCR.

`multiAssC:` a `list` used to store the settings to apply the stock assessment models.

In this case no assessment is used.

`multiBD`: a list with one `FLBDsim` object used to simulate the population growth of the stock `stk2` aggregated in biomass.

`multiBio`: a `FLBiols` object with two elements, one per stock, used to store the biological data.

`multiBioC`: a `list` with one element per stock used to declare the model used to simulate stock dynamics, "ASPG" for `stk1` and "BDPG" for `stk2`.

`multiCv`: a `FLQuants` object used to store the value of the covariates. In this case, it is used to store the economic variables that are not included in the `FLFleets` objects.

`multiCvC`: a `list` used to declare the models used to simulate the covariates and additional parameters needed to feed those models. In this particular case all the covariates are constant along time and the "`fixedCovar`" model is used for all the covariates.

`multiFl`: a `FLFleets` object used to store technical and economic data about the fleets at fleet, metier and stock level. It has two elements, one per fleet, and each of the `FLFleet` objects has two `FLMetier` objects which in turn have two `FLCatch objects.`

`multiFlC`: a `list` used to control the fleet dynamics models, the models used to simulate the short-term dynamics, the catch production, the price formation the capital dynamics and additional parameters needed to apply those models.

`multiMainC`: a `list` used to control the main function at the highest level, the time period of the simulation and the type of management used, simultaneous for all the stocks or independently stock by stock.

`multiObsC`: a `list` used to control the generation of the observed data which includes the generation of the abundance indices and the observation of the stock data. In this case the stock is observed without error and even the numbers and exploitation at age are observed perfectly. No abundance index is observed in this case.

`multiSR`: a list with one `FLSRsim` object corresponding with the `stk1` object, the age structured stock.

6.2.6 `FLBEIA` help page

`FLBEIA` is the main function of the package. Below the help page available in the `R` package is presented. This help page describes the model in brief, the input data needed to run it and the output produced. Furthermore, if provides several examples on how to run FLBEIA using the datasets described in section 6.2.5 and how to analyse the results using the functions in section 6.2.3.

FLBEIA *Run the FLBEIA bio-economic simulation model*

Description

FLBEIA is a simulation model that describes a fishery system under a management strategy evaluation framework. The objective of the model is to facilitate the bio-economic evaluation of management strategies. The model is multi-stock, multi-fleet and seasonal. The simulation is divided in two main blocks, the operating model (OM) and the management procedure (MP). In turn, the OM is divided in three components, the biological, the fleets and the covariables component. The MP is also divided in three components, the observation, the assessment and the advice.

Usage

```
FLBEIA(biols, SRs = NULL, BDs = NULL, fleets, covars = NULL,
  indices = NULL, advice = NULL, main.ctrl, biols.ctrl,
  fleets.ctrl, covars.ctrl, obs.ctrl, assess.ctrl, advice.ctrl)
```

Arguments

biols	An FLBiols object.
SRs	A list of FLSRSim objects. One per age structured stock in biols object.
BDs	A list of FLSRSim objects. One per biomass dynamics stock in biols object.
fleets	An FLFleetsExt object. An extended version of the FLFleet object defined in FLCore.
covars	A list of FLQuants used to store any kind of variables that are used within the simulation and are not stored in the standard objects.

`indices` A list of `FLIndices`. Each element must correspond with one of the stocks in the `biols` object.

`advice` A list with two `FLQuant` elements, `TAC` and `quota.share`. `TAC` is an `FLQuant` with quant dimension equal to the number of stocks in `biols` object, the names used in the quant dimension must be equal to those used in `biols`. `quota.share` is a list with one element per stock in `biols` object indicating the quota share per stock and fleet. The quant dimension of the elements must be equal to the number of fleets and the names used must be equal to those in fleets objects.

`main.ctrl` A list with the settings to control the main function (the year range `sim.years` and the type of management `SimultaneousMngt`).

`biols.ctrl` A list with the settings to control the biological operating model for each stock (the population dynamics model used, additional parameters needed to simulate stock dynamics if necessary).

`fleets.ctrl` A list with the settings to control the operating model for each fleet (the models used to describe fleets' short and long-term dynamics, price model, catch production and additional parameters needed to simulate any of these four processes).

`covars.ctrl` A list with the settings to control the operating model for each covariate (the dynamic model used to describe the each covariate and any additional parameters needed to apply those models).

`obs.ctrl` A list with the settings to control the observation model for each stock (the observation model for the catch and biological data, for abundance indices and additional parameters needed to run the model).

`assess.ctrl` A list with the settings to control how the assessment model for each stock is applied (the assessment model for the stock and the control parameters used to run the model)

`advice.ctrl` A list with the settings to control how the advice is generated for each stock (the HCR for each stock, the reference points used in the HCR and any additional parameters needed to apply the HCRs).

Value

A list with 9 elements: `biols`, `fleets`, `covars`, `BDs`, `advice`, `stocks`, `indices`, `fleets.ctrl` and `pkgs.versions`. All the elements except stocks and `pkgs.versions` correspond with the updated versions of the objects used in the call to `FLBEIA`. '`stocks`' is a list of `FLStock` objects containing the perceived stocks generated in the management procedure to produce the management advice in the last year of the simulation. `pkgs.versions` is a matrix indicating the packages and package version used along the simulation.

Examples

```
## Not run:
library(FLBEIA)
library(FLAssess)          # required to use the IcesHCR.
library(FLash)             # required to use the IcesHCR.
library(ggplot2)


#------------------------------------------------------------------
# Example with 1 stock, 1 Fleets, 1 seasons and 1 iteration: one
#------------------------------------------------------------------

# Load the data to run FLBEIA in a one stock one fleet example using the
# HCR used by ICES in the MSY framework.
data(one)

# The names and the class of the objects needed to run FLBEIA.
# sapply(ls(), function(x) class(get(x)))

# In this scenario a single, age structured, stock is exploited by a
# single fleet with a unique metier.
# The fleet catches yearly exactly the adviced TAC and there is no
# exit-entry of vessels in the fishery.
# The stock abundance and exploitation level is observed without error
# in the observation model.
# There is no assessment model and the TAC advice is used through the
# HCR used by ICES in the MSY framework.

s0 <- FLBEIA(biols = oneBio, SRs = oneSR, BDs = NULL, fleets = oneFl,
```

```
covars = oneCv, indices = NULL, advice = oneAdv, main.ctrl = oneMainC,
biols.ctrl = oneBioC, fleets.ctrl = oneFlC, covars.ctrl = oneCvC,
obs.ctrl = oneObsC, assess.ctrl = oneAssC, advice.ctrl = oneAdvC)


# Names of the object returned by FLBEIA
names(s0)

# The default plot for FLBiol defined in FLCore
plot(s0[[biols[[1]]]])

# Create summary data frames (biological, economic, and catch)
proj.yr     <- 2013
s0_sum      <- bioSum(s0)
s0_flt      <- fltSum(s0)
s0_fltStk   <- fltStkSum(s0)


# Create several plots and save them in the working directory using
# 'pdf' format and 's0' suffix in the name.

plotFLBiols(s0$biols, pdfnm='s0')
plotFLFleets(s0$fleets, pdfnm='s0')
plotEco(s0, pdfnm='s0')
plotfltStkSum(s0, pdfnm='s0')

#------------------------------------------------------------
# Example with several iterations: oneIters
#------------------------------------------------------------

# Load the same data set as before but with 3 iterations.
# Run FLBEIA and plot the results

data(oneIt)


s1 <- FLBEIA(biols = oneItBio, SRs = oneItSR, BDs = NULL,
 fleets = oneItFl, covars = oneItCv, indices = NULL,
 advice = oneItAdv, main.ctrl = oneItMainC, biols.ctrl = oneItBioC,
 fleets.ctrl = oneItFlC, covars.ctrl = oneItCvC, obs.ctrl = oneItObsC,
```

```
 assess.ctrl = oneItAssC, advice.ctrl = oneItAdvC)

# Names of the object returned by FLBEIA
names(s1)

# The default plot for FLBiol defined in FLCore
plot(s1$biols[[1]])

# Create summary data frames (biological, economic, and catch)
proj.yr     <- 2013
s1_bio     <- bioSum(s1)
s1_flt     <- fltSum(s1)
s1_fltStk  <- fltStkSum(s1)

s1_bioQ    <- bioSumQ(s1_bio)
s1_fltQ    <- fltSumQ(s1_flt)
s1_fltStkQ <- fltStkSumQ(s1_fltStk)

s1b_bio     <- bioSum(s1, long = FALSE)
s1b_flt     <- fltSum(s1, long = FALSE)
s1b_fltStk  <- fltStkSum(s1, long = FALSE)

s1b_fltQ    <- bioSumQ(s1b_bio)
s1b_fltQ    <- fltSumQ(s1b_flt)
s1b_fltStkQ <- fltStkSumQ(s1b_fltStk)

# Create several plots and save them in the working directory using
# 'pdf' format and 's1' suffix in the name.

#' plotFLBiols(s1$biols, pdfnm='s1')
plotFLFleets(s1$fleets, pdfnm='s1')
plotEco(s1, pdfnm='s1')
plotfltStkSum(s1, pdfnm='s1')


#------------------------------------------------------------------
# Example with 2 stock, 2 Fleets, 4 seasons and 1 iteration: multi
#------------------------------------------------------------------

# Load the multi data set. This dataset has 2 stocks, one stk1 is
```

```
# age structured and the second one stk2 is aggregated in biomass.

data(multi)

# Run FLBEIA.

s2 <- FLBEIA(biols = multiBio, SRs = multiSR, BDs = multiBD,
fleets = multiFl, covars = multiCv, indices = NULL, advice = multiAdv,
main.ctrl = multiMainC, biols.ctrl = multiBioC, fleets.ctrl = multiFlC,
covars.ctrl = multiCvC, obs.ctrl = multiObsC, assess.ctrl = multiAssC,
advice.ctrl = multiAdvC)

# Names of the object returned by FLBEIA
names(s2)

# The default plot for FLBiol defined in FLCore
plot(s2$biols[[1]])

# Create summary data frames (biological, economic, and catch)

s2_sum      <- bioSum(s2)
s2_flt      <- fltSum(s2)

s2b_flt     <- fltSum(s2, byyear = FALSE)

s2_fltStk   <- fltStkSum(s2)

# Create several plots and save them in the working directory
# using 'pdf' format and 's2' suffix in the name.

plotFLBiols(s2$biols, pdfnm='s2')
plotFLFleets(s2$fleets, pdfnm='s2')
plotEco(s2, pdfnm='s2')
plotfltStkSum(s2, pdfnm='s2')

## End(Not run)
```

6.3 FLBEIAshiny package

The aim of the FLBEIAShiny package is twofold, to provide a tool that can be used by the developers to quickly analyse and present the results and a decision support tool that can be used by the stakeholders.

FLBEIAShiny package launches a Shiny application using the output of FLBEIA directly or from a set of data frames obtained using the functions in Section 6.2.3. In principle, this library could be used with the output of other models as long as the data is arranged in data frames with the same format as those described in Section 6.2.3, but not necessarily with the same output variables. To load this package into an R session it is necessary to install 'coda', 'emdbook', 'kobe', 'reshape', 'shiny' and 'shinyBS' R packages beforehand. These packages are available in CRAN repository (https://cran.r-project.org/).

The package contains only one function , flbeiaApp, which help page is shown in the following section.

6.3.1 flbeiaApp help page

Description

FLBEIAShiny application is an interactive interface to analyse the biological, economic and social indicators obtained through FLBEIA simulation model. It provides lots of graphics at scenario, stock, fleet and metier level to facilitate the analysis of the results and the comparison among scenarios.

Usage

```
flbeiaApp(flbeiaObjs = NULL, RefPts = NULL, bio = NULL,
  flt = NULL, fltStk = NULL, mt = NULL, mtStk = NULL, adv = NULL,
  risk = NULL, years = dimnames(flbeiaObjs[[1]][[1]][[1]]@n)[[2]],
  calculate_npv = NULL, npv = NULL, npv.y0 = NULL, npv.yrs = NULL)
```

Arguments

flbeiaObjs — A named list with a set of FLBEIA outputs, each element of the list corresponding with one scenario. The names of the list are used to name the scenarios.

RefPts — A data frame with columns, 'stock', 'scenario', 'indicator', and 'value', with the values of 'Bmsy','Fmsy', 'Bpa', 'Blim', 'Fpa' and 'Flim' per stock and scenario. If the value for certain stock and/or scenario is not available NA should be used. If the data.frame is not available in the function call the data frame is created internally with `NA`-s in all the cases.

- `bio` The output of `bioSumQ` function.
- `flt` The output of `fltSumQ` function.
- `fltStk` The output of `fltStkSumQ` function.
- `mt` The output of `mtSumQ` function.
- `mtStk` The output of `mtStkSumQ` function.
- `adv` The output of `advSumQ` function.
- `risk` The output of `riskSum` function.
- `years` The years to be included in the application.
- `calculate_npv` logical, should the net present value (NPV) be calculated?
- `npv` The output of `npvQ` function.
- `npv.y0` The first year in the calculation of NPV.
- `npv.yrs` The range of years to be considered in the NPV calculation.

Details

If `flbeiaObjs` is provided most of the other arguments (from `bio` to `npv`) are not needed, they are internally calculated. If it is not provided, it is necessary to provide the rest of the arguments.

Value

The function launches a Shiny-App to analyse the results of `FLBEIA` in an interactive way.

Examples

```
library(FLBEIAShiny)

#------------------------------------------------------------------
# Example with the summary indicators stored in data.frame-s
#------------------------------------------------------------------
```

```
data(FLBEIAShiny)


flbeiaApp(RefPts = RefPts,bio = bioQ, flt = fltQ, adv = advQ,
fltStk = fltStkQ, mt = mtQ, mtStk = mtStkQ, risk = risk,
years = as.character(2010:2024),
calculate_npv = FALSE, npv =  NULL, npv.y0 = NULL, npv.yrs = NULL)



#-----------------------------------------------------------------
# Run FLBEIA first and then use the output to launch flbeiaApp.
# In this case we use the output of FLBEIA directly.
#-----------------------------------------------------------------
library(FLBEIA)
data(oneIt)

one_sc1 <- FLBEIA(biols = oneItBio, SRs = oneItSR, BDs = NULL,
fleets = oneItFl, covars = oneItCv, indices = NULL, advice = oneItAdv,
main.ctrl = oneItMainC, biols.ctrl = oneItBioC, fleets.ctrl = oneItFlC,
covars.ctrl = oneItCvC, obs.ctrl = oneItObsC, assess.ctrl = oneItAssC,
advice.ctrl = oneItAdvC)

# We change the target reference point in HCR and run a second scenario

oneItAdvC$stk1$ref.pts['Fmsy',] <- 0.2

one_sc2 <- FLBEIA(biols = oneItBio, SRs = oneItSR, BDs = NULL,
fleets = oneItFl, covars = oneItCv, indices = NULL, advice = oneItAdv,
main.ctrl = oneItMainC, biols.ctrl = oneItBioC, fleets.ctrl = oneItFlC,
covars.ctrl = oneItCvC, obs.ctrl = oneItObsC, assess.ctrl = oneItAssC,
advice.ctrl = oneItAdvC)

scnms <- c('Ftarget_Fmsy', 'Ftarget_0.15')
stknms <- 'stk1'
RefPts <- expand.grid(
indicator = c("Bmsy", "Fmsy", "Bpa", "Blim", "Fpa", "Flim"),
            scenario = scnms, stock=stknms, value=NA)[,c(3,2,1,4)]
RefPts$value <- c(800, 0.11, 800, 550, 0.25, 0.50,
```

```
                    800, 0.2, 800, 550, 0.25, 0.50)

flbeiaObjs <- list(Ftarget_Fmsy = one_sc1, Ftarget_0.15 = one_sc2)


flbeiaApp(flbeiaObjs = flbeiaObjs, RefPts = RefPts,
          years = ac(2000:2025), calculate_npv = TRUE,
          npv.y0 = '2012', npv.yrs = ac(2013:2025))
```

6.3.2 Appearance

Figure 6.1 shows the main page of the `FLBEIAShiny` application. It is the page that emerges when the call is done from the R session. The 'about' page gives a short description of `FLBEIA` and the 'simulations' dropdown gives access to the summary output variables at different levels. In the dropdown, there is one link for each of the summary indicator categories:

Stocks: page with the stock output variables. It has three plot types available that are displayed in different sub-pages, 'Time Series', 'Kobe plot' and 'Biological risk'.

Fleets: page with the fleet output variables. It has three plot types available that displayed in different sub-pages, 'Time Series', 'Net Present Value' and 'Economic risk'.

Fleets by stocks: Page with fleet output variables related with the stocks. Only plots of time series are available in this page.

Metiers: page with output variables at metier level. Only plots of time series are available in this page.

Metiers by stock: page with metier output variables related with the stocks. Only plots of time series are available in this page.

Summary: page with a summary plot of the biological and economic results.

Advice: page with the output variables related with the advice. Only plots of time series are available in this page.

The time series plots are the same for all the output variables (Figure 6.2). The lines correspond with the quantiles provided in the data frames or the 5%, 50% and 95% in case they are calculated internally. The shaded area corresponds with the confidence interval between the two quantiles and the line in the middle with the median. The output variables, stock or fleets, and scenarios are selected in the left

Figure 6.1: Main page of the FLBEIA Shiny application.

hand side of the window. For each combination of indicator and stock or fleet there is one panel and the scenarios are plotted in the same panel using different colors. As the value of the output variables can have very different scale the plots can share the same scale or not using the bottom in the left hand side.

At stock level there is the option of generating Kobe plots (Nishida et al. 2011) (Figure 6.3). The Kobe plot divides the $[0, \infty)^2$ area in four quadrants. The x-axis represents the ratio between the SSB and the SSB reference point at MSY. In turn, the y-axis represents the ratio between the fishing mortality and the fishing mortality reference point corresponding to MSY. The green quadrant, $[1, \infty) \times [0, 1)$ corresponds with the area where the stocks are exploited sustainably, i.e., the SSB is above the reference level and the fishing mortality is below it. The yellow quadrants correspond with the stock being overfished ($F > F_{msy}$ but $SSB > B_{msy}$, i.e, $[1, \infty) \times [1, \infty)$) or suffering of overfishing ($F < F_{msy}$ but $SSB < B_{msy}$, i.e, $[1, \infty) \times [0, 1)$). The red quadrant corresponds with the area where the stock is being overfished and suffering of overfishing, i.e. $[0, 1) \times [1, \infty)$.

The biological risk window shows the probability of SSB being below a given precautionary (pBpa) or limit (pBlim) reference point (Figure 6.4). The plots are time series of the probabilities over time. Similar plots are also available, only at fleet level, for the probability of the profits being below a given threshold. There

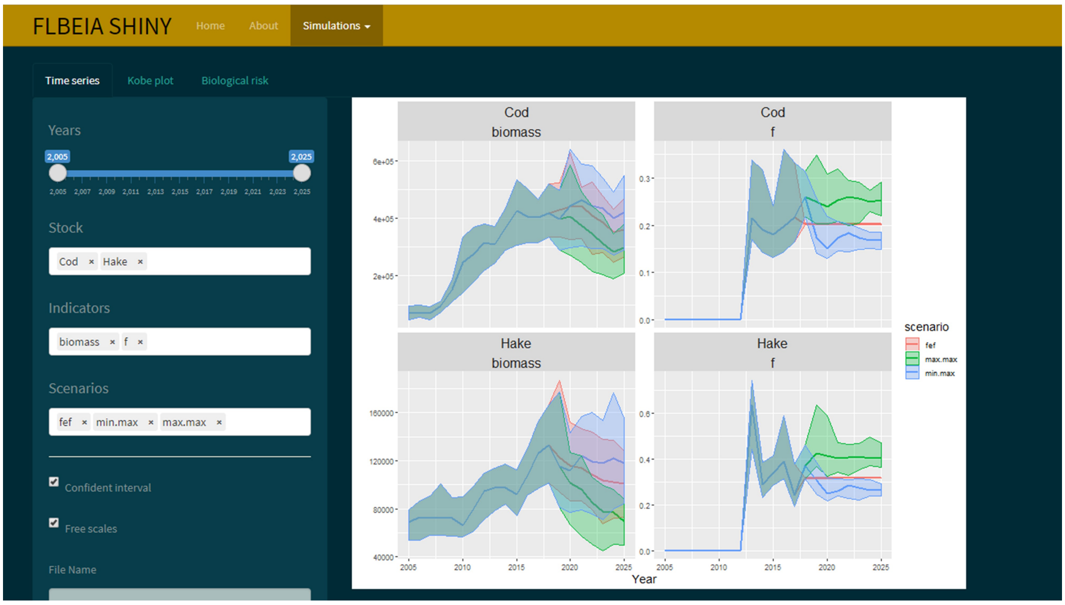

Figure 6.2: Time series plots for biomass and fishing mortality (f) output variables for Hake and Cod stocks.

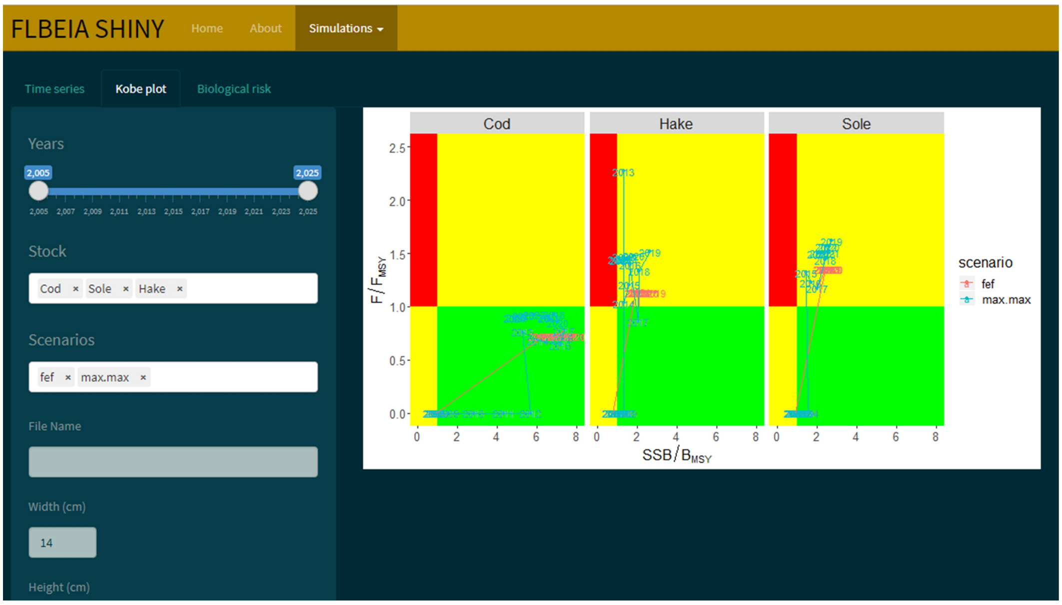

Figure 6.3: Kobe plot of cod, hake and sole stocks.

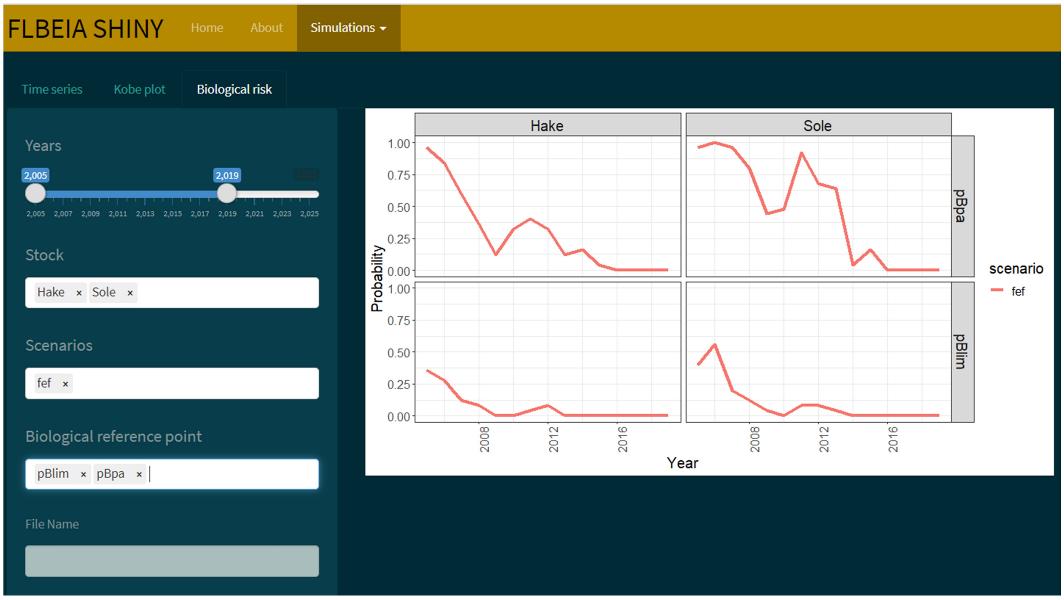

Figure 6.4: Risk plots.

is one panel per stock or fleet and the scenarios are drawn in the same panel using different colors. The stock, fleets, output variables and scenarios are selected in the left hand side.

The results in each scenario are summarized using the polar plots in the summary page (see Figure 6.5). These plots are divided in four quadrants and each one correspond with one indicator SSB, fishing mortality, gross surplus and capacity. In each quadrant the fleets or the stocks are represented with triangles of different colors. The area of the triangle is proportional to the ratio of value of the indicator in the last year and the reference value. If the triangle is equal to the circle it means that the value of the indicator in the last year of simulation and the reference period is the same. Each plot corresponds with one scenario and the scenarios are selected in the left hand side of the plot.

All the plots can be downloaded using the option in the bottom of the left hand side of the page (Figure 6.6). There are several formats available to save the plots. The size and the name of the plot are selected by the user. The scale is used to change the size of the text in the plot and corresponds with the argument scale in the `ggsave` function in `ggplot2` `R` package.

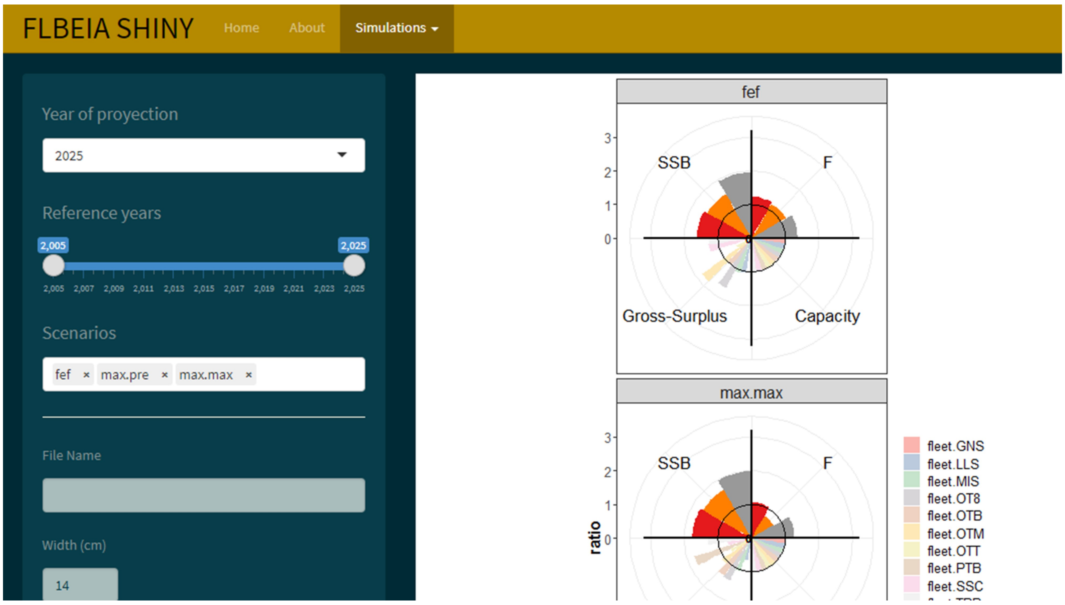

Figure 6.5: Polar plots. In each quadrant a different indicator is shown, spawning stock biomass (SSB), fishing mortality (F), gross surplus and capacity. The circle represents the *status quo* situation.

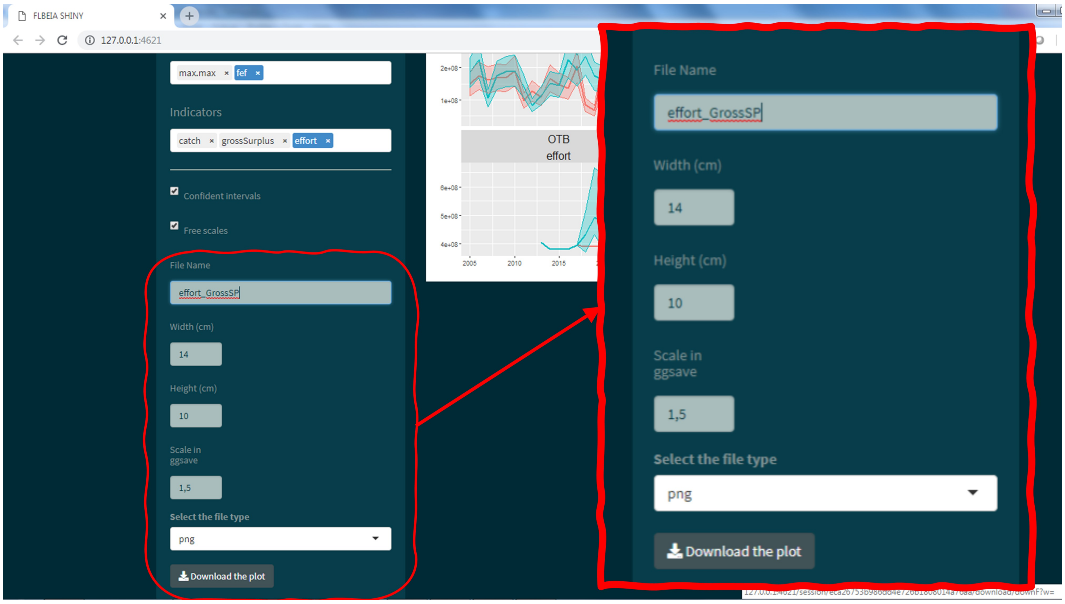

Figure 6.6: All the plots can be downloaded using the options in the left hand size of the page.

6.4 Calibrated visual selection and convergence criteria in practice

The *calibrated visual* selection criterion defined in Section 3.2.1 has been implemented in R using two functions, `selection_criterion` and `selection_criterion_boot`. The first one calibrates the selection criterion based on a *visual* selection of the input factors, i.e, it calculates de values w_D, w_F and w_H defined in Section 3.2.1. Then, the second function uses the weights calculated by the first function to apply the *calibrated visual selection* criterion to a bootstrap sample of the Morris AEEs. Hence, for each bootstrap iteration, it returns the set of factors selected with the *calibrated visual* criterion.

Thus, to apply the convergence criterion it is enough to produce bootstrap samples of the AEEs increasing the number of trajectories used until the number of factors selected with the selection criterion, $\mathbb{F}_r$ do not change when the number of trajectories are increased.

To use the `selection_criterion` function, first we need to define the arguments of the function K_{EE}, N_{boot} and ν, for example:

```
K_EE  <- 15
Nboot <- 500
nu <- 0.95
```

Afterwards we have to carry out a *visual* selection of the input factors to identify the set $\mathbb{F}_{vis}$. For doing so, first we plot the AEE for each of the output variables, in this example, the SSB, recruitment and catch of hake and horse mackerel. As an illustrative example, only the 15 factors with the highest AEE are plotted.

We select the factors in such a way that the selected input factors for each output variable differentiate from the rest of the factors and they result in the cardinality of $\mathbb{F}_{vis}$ equal to $K_{EE} = 15$:

```
Nvis <- c(ssb_HKE = 3,   ssb_HOM = 2,
          rec_HKE = 2,   rec_HOM = 4,
          catch_HKE = 4, catch_HOM = 3)
```

And we identify the input factors selected in the *visual* selection.

```
Fvis <- unique(unlist(lapply(names(Nvis), function(id)
as.character(subset(AEE, outVar == id)[1:Nvis[id],'name']))))
```

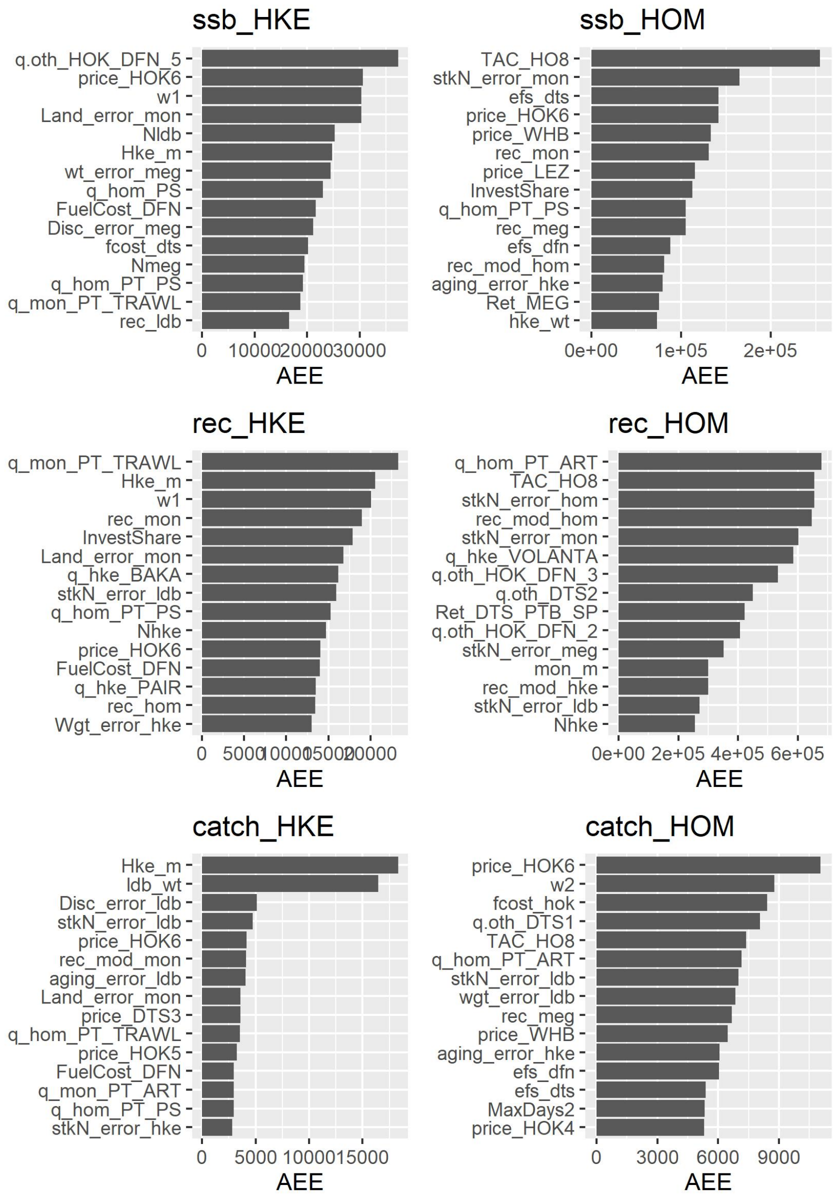

Figure 6.7: Barplots with the AEEs for six output variables the spawning stock biomass (ssb), recruitment (rec) and catch of hake and horse mackerel. Only the 15 factors with the highest AEE are plotted.

```
Fvis
[1]  "q.oth_HOK_DFN_5" "price_HOK6"      "w1"          "TAC_HO8"
[5]  "stkN_error_mon"  "q_mon_PT_TRAWL"  "Hke_m"       "q_hom_PT_ART"
[9]  "stkN_error_hom"  "rec_mod_hom"     "ldb_wt"      "Disc_error_ldb"
[11] "stkN_error_ldb"  "w2"              "fcost_hok"
```

Once we have the visual selection we use the function `selection_criterion` to calibrate the selection criterion to obtain parameters, $\delta_{\mathrm{F}}, \delta_{\mathrm{H}}, \delta_{\mathrm{D}}$ $w_{\mathrm{F}}, w_{\mathrm{H}}$ and w_{D} needed to apply the selection criterion:

```
FM <- selection_criterion(AEE, K_EE, Nvis)
```

To ensure the convergence of the method we apply a bootstrap to the *calibrated visual* selection criterion using `selection_criterion_boot` function. We start using 25 trajectories and increase the number gradually until we see that the number of input factors selected does not vary. With 25 trajectories, 5 input factors are selected in more than 95% of the bootstrap iterations.

```
load('./example/AEE_Boot_25.RData')

F25_all <- selection_criterion_boot(AEEboot, K_EE, FM$weights)
Bootstrap iteration:  1
Bootstrap iteration:  2
Bootstrap iteration:  3
.
.
.
Bootstrap iteration:  500

F25 <- names(F25_all[which(F25_all>=alpha*Nboot)])
length(F25)
[1] 5
```

We apply the same process: the *visual* selection, the calibration and the bootstrap for $50, 100 and 150$ trajectories and we see that the method converges with 100 trajectories and 10 input factors are selected: `"Hke_m"`, `"Hom_m"`, `"hom_wt"`, "rec_hke", "rec_mod_hom", "efs_dts", "rec_mod_hke", "hke_wt", "rec_hom" and "Nhom". .

An R script with the whole code and the data needed to run it is available in github https://github.com/dorleta/robust_Morris_Sobol and zenodo Garcia (2019).

6.5 Shiny application for Global Sensitivity Analysis results

The complete set of plots of the GSA conducted in Chapter 5 are presented in a Shiny application explicitly developed to present these results. The application is accesible in https://aztigps.shinyapps.io/GSAApp/ with the password 'flbeiaGSA'. The plots are divided in two pages, the plots corresponding with the results of Morris elementary effect method and the plots corresponding with the results of the Sobol variance decomposition method. In turn, for each of the methods the plots are divided in two groups, the plots corresponding with the stock's output variables and the plots corresponding with the fleet output variables. The stocks, fleets and output variables are selected using the buttons available in the left hand side of the page. In each page several plots can be plotted and the configuration of the page is defined by the user; the variables that appear in the columns and the rows, the output variables, and the stocks or the fleets. This feature is specially important to facilitate the identification of patterns at indicator, stock or fleet level depending on how they are displayed. The number of factors displayed can be selected by the user and only the factors with the highest AEE or importance index are shown. The value of the elementary effects and the importance indices are represented in barplots, ordered according to its value from the highest to the lowest.

In the case of Morris method, the factors selected with each criterion can be visualized selecting the criterion in the left hand side of the web page (Figure 6.7). When a criterion is selected, a vertical line is drawn which divides the factors in two groups, the factors selected by the criterion on the right of the line, and the non-selected ones on the left of the line.

In the case of Sobol variance decomposition method there are two bars. When the bars are not stacked the blue bars correspond with the *total-effect* indices (Figure 6.9). In both cases, the *first-order* indices correspond with the red bars, but when the bars are stacked, the *total-effects* are represented with the sum of both bars, the

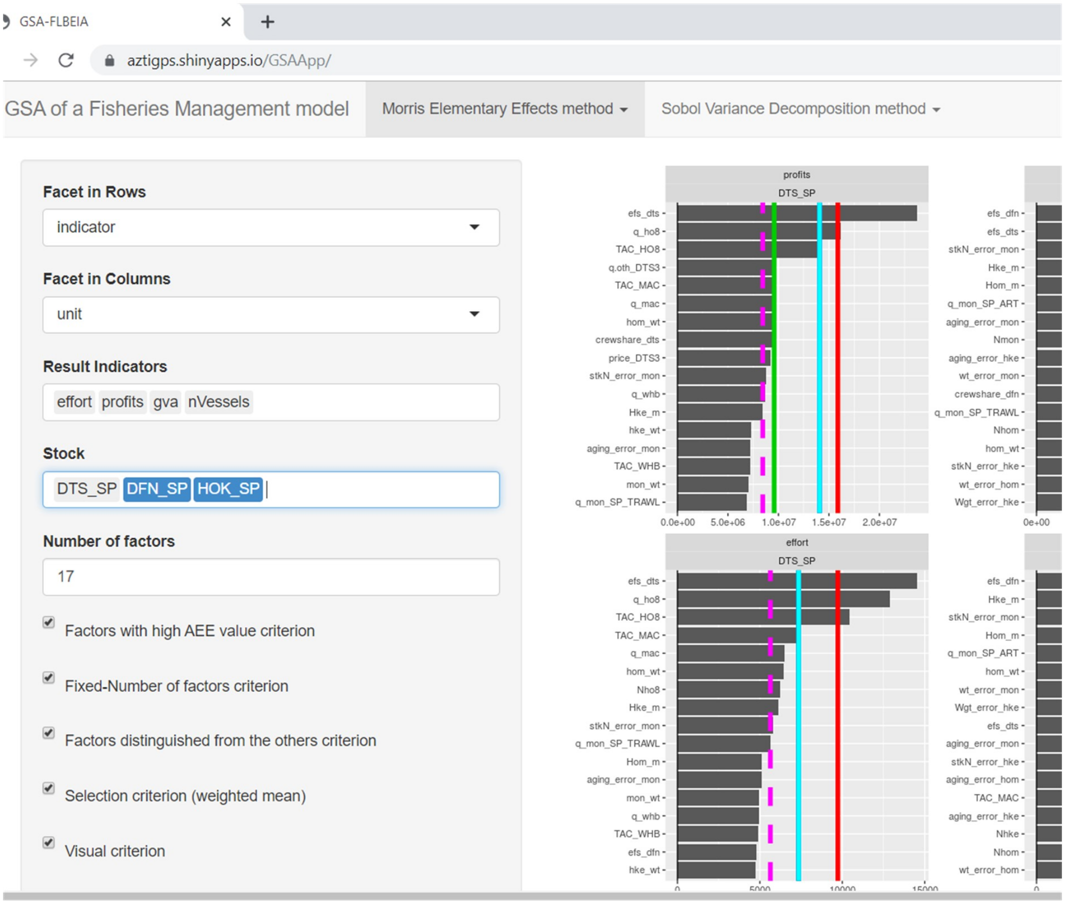

Figure 6.8: Barplots of the Morris elementary effects. The horizontal lines correspond with the selection criteria. Due to the restriction in space only part of the page is shown.

blue and the red ones (Figure 6.10). In the left hand side menu of the web page the user chooses how to show the bars. Furthermore, if the option is non-stacked there is the option of plotting the 95% confidence intervals (the black lines in Figure 6.10). The number of factors shown for each indicator can be selected using the desired number of factors or the desired group of factors in the 'set of factors menu' (the factor related with a certain stock distinguished by the acronym of the stock,the economic factors 'ECO', the technical factors 'TEC', the factors related with the catch advice 'ADV' and the factors related with the observation error 'OBS').

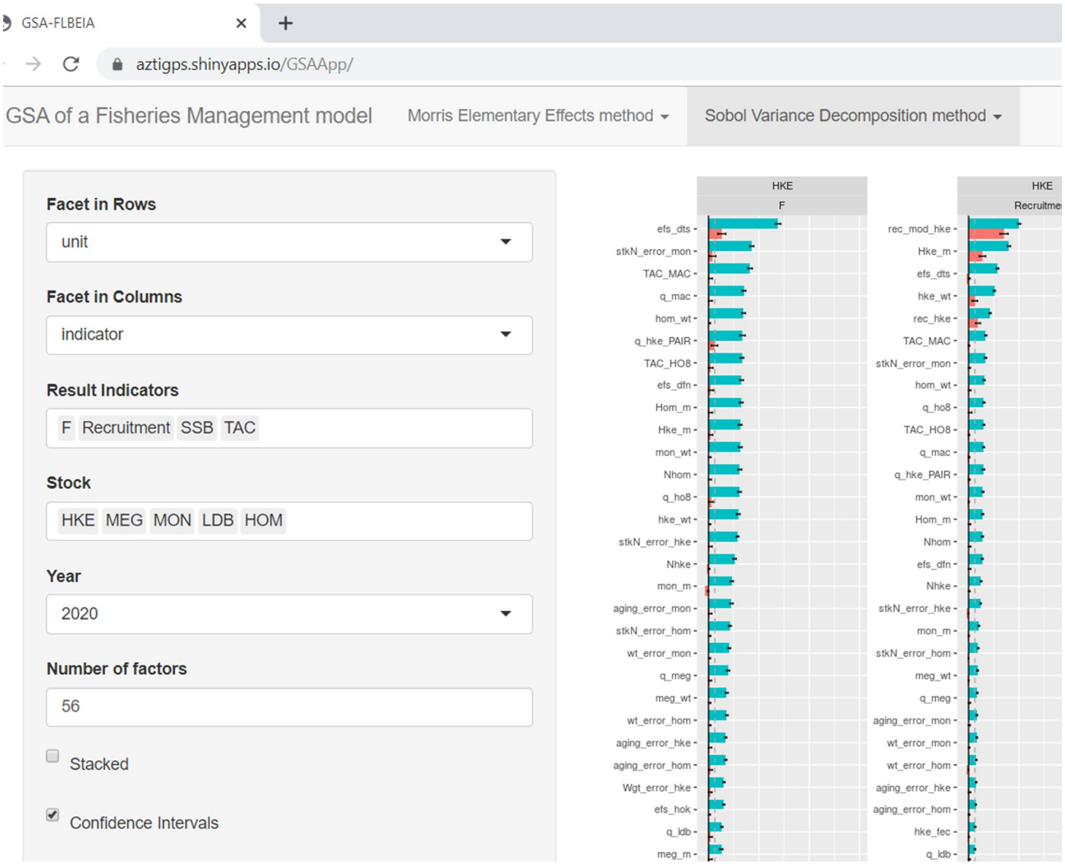

Figure 6.9: Barplots of the Sobol variance decomposition indices. The red bars corresponds with the first order indices and the blue ones with the total indices. The black segments represent the 95% confidence intervals. Due to the restriction in space only part of the page is shown

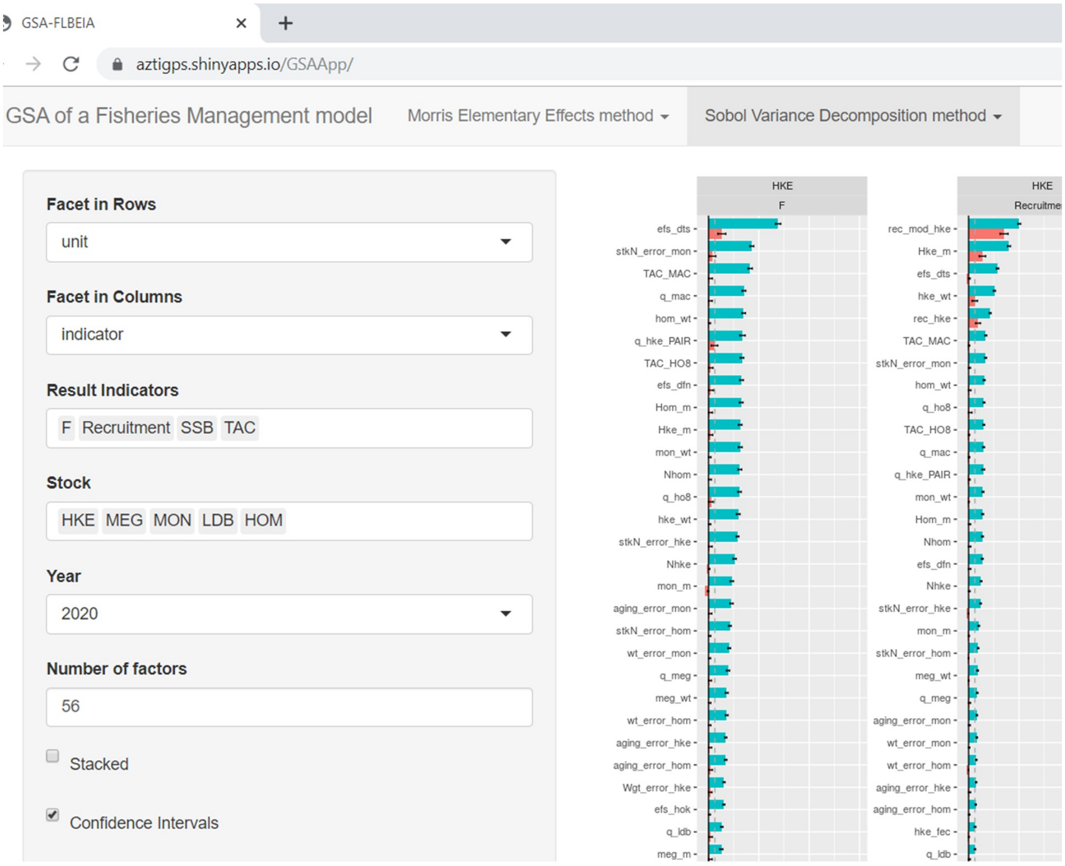

Figure 6.10: Barplots of the Sobol variance decomposition indices. The red bars corresponds with the first order indices and the blue ones with the total indices. The black segments represent the 95% confidence intervals. Due to the restriction in space only part of the page is shown

Chapter 7

Conclusions and future work

7.1 Conclusions

7.1.1 Use, application and validation of `FLBEIA`.

Use Nowadays, the use of `FLBEIA` has been extended beyond the development team. Furthermore, it has become one of the most used bio-economic simulation models to support the fisheries management decision making process in Europe. In practice, the flexibility and utility of `FLBEIA` has been demonstrated by the large number of case studies in which it has been applied.

`FLBEIA` includes the two most common structures used to model the growth of fish populations: age and total biomass structures. The growth of the former is modelled using the exponential survival model based on Lotka (1922) and McKendrick (1926), and the latter using a model based on Verhulst (1838). The short-term dynamics of a fleet can be modelled using models based on tradition or profit maximisation. These models have been used to model fleets that target a single stock (Sánchez et al. 2018), as well as mixed fisheries where a set of stocks are caught simultaneously (Garcia et al. 2017a) and sequential fisheries, which are a specific case of mixed fisheries but with a strong seasonal component (Andres et al. 2020). For the long-term dynamics, only the model described in Salz et al. (2011) is included in `FLBEIA`. In the literature, these models have received less attention and their practical use in bio-economic models is scarce (Nøstbakken et al. 2011).

In the MP, the observation of all the variables simulated in the OM can be subject to error. In the application of GSA in this thesis, we saw the usefulness of including these errors explicitly in the simulation. Several assessment models (`FLa4a`, `FLXSA` and SPiCT) can be already used within FLBEIA. SS3 (Methot Jr and Wetzel 2013) and Bayesian models implemented in JAGS (Plummer 2003) have been also used for the Iberian sardine (ICES 2019) and for cod in the Northwest Atlantic (González-Troncoso et al. 2015), respectively. However, their use has not been generalised in FLBEIA, in the first case, because the model is too complex and has many options to configure the fit, and in the second, because the model itself is case specific. FLBEIA includes a wide range of HCRs which return catch advice for the stocks. They can be model-free or model-based, depending on whether they use the output of an assessment model to generate the advice or an abundance index. Recently, a multi-stock harvest control rule has been implemented which is applied to a set of stocks simultaneously (Garcia et al. 2019b). Additionally, technical management measures can be also simulated, for example Prellezo et al. (2017) analysed a change in the mesh size of the trawler fleet. Effort-based management can also be simulated, defining the overall effort as an input factor.

The use of FLBEIA has been focused on providing scientific advice and on conducting scientific research. The main implementations of FLBEIA carried out over the years are listed in Table 7.1. Its extended use has led us to teach three international courses since 2017, and in 2020 we have a fourth course already planned. The model has awakened the interest of other scientists not only for the application of the model but also for collaboration in new developments. Within the MARES European project (http://www.mares-eu.org/), we are collaborating with a research team to show the value added of using realistic models of fleet dynamics in the decision making process. As a result of this collaboration, new models of fleet dynamics will be coded in FLBEIA. Moreover, we are collaborating with the Institute of Marine Research in Norway to link FLBEIA with the Gadget multi-species model.

One of the strengths of FLBEIA is that it is built using FLR libraries. FLR is a collaborative project oriented towards developing quantitative fisheries management tools. Since the preliminary versions of the basic FLR libraries, more than 10 years ago, its use for exploratory data analysis, stock assessment, bio-economic modelling and MSE has been extended among fishery scientists, especially in Europe. According to Google Scholar, the FLR article (Kell et al. 2007) has been cited more than 290 times since 2007, a significant number of those papers use FLR to carry out their analysis and have been published in peer reviewed journals. Most of them involve some kind of MSE and a few present generic methods implemented as R packages (R Core Team 2019). Jardim et al. (2014b) present a new stock assessment model, Ulrich et al. (2011) and Poos et al. (2010) fleet dynamics models, and Jardim et al.

Table 7.1: Main applications of FLBEIA in working groups, international projects and other research activities.

Activity	Entity	Description	Reference
Advice	ICES	Generation of mixed fisheries management advice in ICES	ICES (2018b)
Advice	STECF	Evaluation of mixed fisheries multi-annual management plans for Western Waters	STECF (2015b)
Advice	STECF	Evaluation of the management plan for Bay of Biscay Anchovy together with stakeholders	Sánchez et al. (2018), STECF (2014)
Advice	ICES	Evaluation of rebuilding strategies for Iberian Sardine	ICES (2019)
Advice	NAFO	Development of a MSE for cod in division 3M	González-Troncoso et al. (2015)
Research	DAMARA project	Development of a scientific decision support tool for mixed fisheries in the Celtic Sea	EC (2016)
Research	STECF	Contrast FLBEIA against flexibility, applicability and utility criteria. Recommendations used to improve FLBEIA development	Jardim et al. (2013)
Research	DeepFisMan Project	Management strategies for three deep-water case studies	Garcia et al. (2013)
Research	MyFish project	Bio-economic performance of multi-stock reference points for mixed fisheries. Modelling approach validated by stakeholders	Garcia et al. (2017a; 2015)
Research	DrumFish Project	Multi-stock harvest control rule to produce consistent catch advice for mixed fisheries	Garcia et al. (2019b; 2016)
Research	AZTI	Sampling priorities for Iberian Waters demersal fishery	Garcia and Prellezo (2016)
Research	AZTI	Bio-economic impact of changing the mesh size in a trawler fleet	Prellezo et al. (2017)
Research	Discardless	The good and the bad side of the landing obligation policy in European waters	Prellezo et al. (2016)
Research	DrumFish Project	Bio-economic impact of the common fisheries policy in the North Sea demersal fishery	Taylor et al. (2018)

(2014a) HCRs. All these developments can be directly integrated into `FLBEIA`.

We believe that the main reasons for the extensive use of `FLBEIA` are: its being part of the R and `FLR` (Kell et al. 2007) projects, its use of standard input data formats, its having extensive material to help new users implement their own case studies, and the great dedication of the `FLBEIA` team in both applying it in a broad range of case studies and in helping new users.

Last but not least, it is being used as part of three doctoral theses to contribute to answer research questions about the behaviour of fishers in mixed fisheries, the management of the Bay of Biscay sardine, and the management of data limited stocks in mixed fisheries.

Application The application of `FLBEIA` described in Chapter 4 shows the usefulness of these type of models in informing the policy making process. In particular, it demonstrated how the definition of alternative reference points could mitigate the negative economic impact of the landing obligation policy while ensuring the sustainability of fish stocks.

When subjected to the landing obligation, if selective fishing is not possible, the quotas of limiting stocks become an input management factor, i.e. they determine the amount of effort that the fleets are able to execute. In this regard, the loss in profits generated by the implementation of the landing obligation in some fleets is not only generated by the loss in the landing of the stocks subject to the TAC and quota system but from the loss in the landing of other valuable stocks for which there is no catch restriction, but of which the catch is limited by the limitation in effort generated by the restrictive stocks.

If the landing obligation were fully implemented and enforced, current distribution of catch quota shares together with the incapacity of the fleets to be fully selective would prevent a full use of fishing opportunities. Hence, the landing obligation should be accompanied by a management system that ensures consistency between single-stock TACs at the fleet level to ensure the full use of fishing opportunities.

The selectivity of the fleets was calculated using the catch and effort data obtained through the European data collection framework. The detail provided by this data in relation to the inter-species selectivity of the fleets could be too coarse to obtain an adequate description of the real capacity of fishers to discriminate between stocks in their fishing operations. Ideally, the data should be provided at fishing operation level, but this could only be attained if fishermen recorded the composition of the catch in each operation. Nevertheless, video sampling together with machine learning open a range of possibilities in this field.

Validation The validation of `FLBEIA` has been carried out mainly on four sides: the systematic checking of the code, an extensive use of the model in diverse case studies, the presentation of the model to stakeholders and the GSA carried out in this thesis.

The GSA conducted as part of this thesis constituted a breakthrough in the validation process of bio-economic models providing scientific advice in fisheries management. It provided a deep understanding of the behaviour of the model and an invaluable tool to identify how the input factors drive the dynamics of the output variables. Furthermore, it estimated the contribution of the input factors to the variance of the output variables and the overall variance. The estimates of the *generalised* sensitivity indices provided a ranking of the overall contribution of the input factors to the output variance, which, in turn, provided a scientific basis to prioritise the research effort needed to make advances in the knowledge of the functioning of this fishery system in particular.

7.1.2 Selection and convergence criteria

We defined a selection and a convergence criteria to ensure a robust combination of the Morris and the Sobol methods. Furthermore, these criteria could be used with other elementary effect screening methods and computationally costly GSA methods. On the one hand, the *calibrated visual criterion* mimics the *visual* selection criterion. On the other hand, the convergence criterion was specifically defined to ensure the convergence of the Morris method when the objective is to select a maximum number of input factors. While the selection criterion outperformed other existing criteria, the computing load required to achieve convergence with the new convergence criterion was lower than that needed by criteria related with other objectives.

The selection criterion provides an objective and robust way of selecting the most important input factors in the Morris method. The criterion needs to be calibrated using a *visual* selection in an initial application of the method but then it can be applied automatically. Such automating is essential to assess the convergence by means of bootstrap. Furthermore, it is also useful when there are several output variables because it allows applying the same criterion in the selection of input factors for all the variables and avoids the inconsistencies that could arise with the *visual* criterion.

If the aim is to explain the variance of every single output variable or the number of input factors to be selected is high, the *calibrated visual* criterion is always better than the other criteria used in the literature (*fixed number of factors* and *Savage* criteria). However, if the interest is to select the input factors that are the most important at an overall level, even if the input factors that explain a significant part of the variance of a single output variable are left out and the number of input factors to be selected is low, the *Savage* criterion (Campolongo et al. 2007, Savage 1956) performs better than the *calibrated visual* criterion.

7.1.3 Global sensitivity analysis of fisheries management simulation models

The computational cost of the Sobol method increases exponentially with the number of input factors. Hence, it is extremely important to condition the model efficiently, so that the effective number of input factors is kept as low as possible. In Chapter 3 we approached the problem of reducing the number of input factors from two sides: the robust combination of the Morris and the Sobol methods and the reduction in the number of input factors through an efficient conditioning of the model. The guidelines proposed to condition the model efficiently also remove the correlation between some of the input factors, allowing the use of standard GSA methods. Additionally, we proposed other guidelines to deal with observable variables in the MP, and to reduce the computational burden of the variance decomposition method looking at the convergence of the sensitivity indices of individual input factors. Thus, this thesis contributes to fight one of the biggest drawbacks of the method, its high computational cost, and also facilitates the use of the standard methods.

Multi-stock and multi-fleet fisheries management simulation models usually have hundreds of input factors. Performing an adequate uncertainty conditioning including all the input factors would be practically unaffordable. As done here, the GSA can be applied with wide confidence intervals in the input factors, and subsequently, use the results to guide the effort in the uncertainty conditioning of a reduced number of input factors.

Local sensitivity analysis is usually used in fisheries management simulation models (Essington 2007, Ives et al. 2013, Mackinson et al. 2003) and elsewhere (Saltelli et al. 2019) to assess the impact of variability in the input factors in the output variables. Here, we have proved that local sensitivity analysis is not adequate for `FLBEIA` because the output variance was explained largely by the interaction between input factors and local sensitivity analysis ignores the effect of the interaction between input factors. Hence, local sensitivity analysis would result in an underestimation of the importance of the input factors. Many fisheries simulations models use the same mathematical models used in `FLBEIA` to describe the processes that build them up. Hence, for those models local sensitivity analysis would be also invalidated with this analysis.

Even if included by the European Commission in the impact assessment guidelines (EC 2009), the routine application of this type of approach in the framework of impact assessment would be compromised due to the time available to carry out the whole impact assessment process. If even with the guidelines proposed in this thesis the cost of applying the variance decomposition method is unaffordable and the purpose of the analysis is only to identify the most influential factors in the model, the Morris method could be a good approximation to the more informative variance decomposition approach (Gan et al. 2014, Ikonen 2016, Kristensen and Petersen 2016). To improve the estimation of the importance indices, the sampling in the Morris method could be replaced by the radial sampling proposed by Campolongo et al. (2011).

7.1.4 Global sensitivity analysis in practice

The GSA provides valuable information for understanding the inner behaviour of `FLBEIA`. It provides information about the direct effect of the input factors and the effect of the interaction between factors on the output variables. Furthermore, this information revealed the importance of the processes that build up the model. For example, the short-term dynamics of the fleets were revealed to be a key component in the model, as already noted by other authors (Fulton et al. 2011a). In contrast, the importance of the stock-recruitment process, which is usually considered one of the most important processes (Rademeyer et al. 2007), was proved to be lower than expected. The general patterns observed in the sensitivity indices were largely explained by the models used to describe the dynamic of the system. For example, the Morris method discarded most of the economic indicators because the fleet dynamics were not constrained by economic incentives. Regarding the management process, the analysis showed that an improvement in the management process, through a higher accuracy in the observable variables and stock status estimates, would impact directly on the catch advice and fleets' indicators, such as effort or profits, but would have a minor impact on biological indicators.

GSA has proven to be a useful tool to identify the stocks for which accurate assessment is required in the framework of mixed fisheries. The stocks that drive the fleet dynamics (the target stocks) should be accurately assessed. But the uncertainty in the assessment of the non-target (secondary) stocks has little impact on the performance of the bio-economic system and the accuracy in its assessment is not that important. However, this does not mean that the non-target stocks could be managed exclusively through the management of target stocks in a mixed fisheries framework. Non-target stocks need to be monitored and managed by specific measures because otherwise the absence of management could create incentives to over-exploit them. Furthermore, we suspect that the result could be related with the short-term dynamics of the fleets.

Although the GSA has been applied in a particular case study, many of the conclusions can be extrapolated to other `FLBEIA` model implementations, or similar model implementations, whenever the stock and fleet dynamics are governed by similar conditions.

In summary, this thesis not only provides a tool to support the decision making process in fishery management but also a set of guidelines for improving the way fisheries simulation models are used in practice.

7.2 Further work

7.2.1 Economic equilibrium models

The economic variables used in bio-economic fisheries simulation models are usually maintained constant along time and conditioned based on past data. However, fish prices and salaries, for example, are the consequence of an equilibrium in the market (the supply and demand). In recent years, fisheries simulations models that estimate the economic indicators dynamically based on the future expectations of the fishers have been developed. A detailed description of these models can be found in Da-Rocha et al. (2017) . However, these models cannot be integrated directly with `FLBEIA` because the two modelling approaches are different. While `FLBEIA` is discrete in time and uses equations in differences to describe the dynamic of the fishery system, the model in Da-Rocha et al. (2017) is continuous and uses partial differential equations. However, under the principle of rational expectations they could be made compatible. The model in Da-Rocha et al. (2017) can be applied at each time step to dynamically update the prices based on the rational expectations of the fishers. Then, the other components of `FLBEIA` could be executed independently. Nevertheless, this is a simplification of what is really needed. The link between both models is not straightforward and coupling both approaches requires further research.

7.2.2 Link of `FLBEIA` with the Gadget model.

The `FLBEIA` development team is collaborating with the Norwegian Institute of Marine Research to link it with the multi-species model Gadget (Begley 2004). This link would provide length structure and trophic interactions to `FLBEIA`'s biological OM. This development would make the biological OM of `FLBEIA` much more general and it would make `FLBEIA` occupy a prominent position among ecosystem models of intermediate complexity. The model will need to be tested and put into practice in a real case study. However, conditioning such a complex model is not straightforward and will require a big research effort in defining the stocks and their interactions among others.

7.2.3 Metamodels

Metamodels are statistical approximations of simulation models in which the execution time is negligible in comparison with that of the original model (Barton 1998, Coutts and Yokomizo 2014). They are usually used to approximate complex simulation models to address the problem of their computational burden. In GSA they have been extensively used to calculate sensitivity indices (Gratiet et al. 2016, Marrel et al. 2009). In some cases, depending of the form of the metamodel, the sensitivity indices can be calculated analytically, and the computational cost of the analysis is thus reduced to the cost of adjusting the metamodel. In the framework of `FLBEIA`, metamodels could be useful in two areas: in the calculation of sensitivity indices and in the real-time application of `FLBEIA`. On the one hand, the metamodel could enormously reduce the cost of the sensitivity analysis and would allow calculating high order sensitivity indices. On the other hand, if the metamodel provided a good enough `FLBEIA` fit and executed quickly, it could be used in life sessions with stakeholders to test alternative hypotheses about the system dynamics and management strategies on demand. Nowadays, a battery of scenarios needs to be run beforehand to be able to show a wide range of alternative scenarios.

A possible drawback of metamodels could be the effort needed to build them, which may not compensate for the computational saving in the estimation of the sensitivity indices. However, the development of a statistical framework to facilitate building metamodels for particular `FLBEIA` implementations could reduce the effort needed to build the metamodels in practice. The metamodels would promote the application of GSA methods. Moreover, they would be an invaluable tool to interact with stakeholders in the definition of fishery management strategies.

7.2.4 Assessment of data-limited stocks

In this thesis we found that the combination of GSA and MSE can be used to identify the stocks for which the accuracy in the assessment could be relaxed. In many fisheries the number of exploited stocks is so high that it is practically impossible to have quantitative assessments for all of them. Traditionally, the most commercial valuable stocks were only assessed. However, in the last decade there has been a tendency to increase the number of stocks assessed. As having enough data to apply traditional stock assessment models is usually impossible for all the stocks, the research on the assessment and management of data-limited (also known as data-poor) stocks became a hot topic in the last decade (Carruthers and Hordyk 2018, Chong et al. 2019, Dowling et al. 2019, Kokkalis et al. 2017). However, there are still many stocks without reliable quantitative assessments. In this framework, a robust method for identifying the stocks for which stock assessment is not needed to guarantee a sustainable exploitation, could provide a scientific basis to efficiently allocate the research effort of stock assessment.

However, the simulations carried out in this thesis were not designed to identify those stocks; the finding was incidental, indeed. Hence, further research would be needed to prove that the assessment of some stocks could be relaxed or even eliminated. The design of the scenarios and their conditioning should be focused on determining under which conditions and assumptions the assessment of a certain stock can be removed. Based on the results obtained, we can anticipate that the answer to this question will depend largely on the model used to describe fleet dynamics. Moreover, the uncertainty in effort share, one of the key parameters in fleet dynamics models, is the input factor with the biggest contribution to the overall variance. Hence, it could be necessary to apply GSA to scenarios with different fleet dynamics. Additionally, the uncertainty conditioning of the model, and especially that of the errors in the assessment and parameters of the fleet dynamics, should be carried out cautiously to obtain reliable results.

7.2.5 Uncertainty conditioning

In the application of the GSA in Chapter 5, as done usually in the literature, we used the same CV and probability distribution to condition the uncertainty in all the input factors. A more detailed approach would require adjusting the CV and the distribution to the observed data and prior knowledge. However, in most of the cases the available data and time precludes to perform a detailed uncertainty conditioning. The application presented in Chapter 5 proved that uncertainty conditioning could be focused exclusively on the 26 input factors that had a significant contribution to the output variance. The rest of the input factors could be conditioned using their mean value. Carrying out a complete uncertainty conditioning for the 26 input factors will provide an improved sensitivity analysis compared to the one carried out in this thesis. However, the research on uncertainty conditioning should be expanded to advance in the uncertainty conditioning of fishery simulation models in general with special attention to the conditioning of the correlation between input factors. Although it is usually assumed that most of the input factors are independent, many of them are in fact correlated. Correlation between input factors could prevent the use of traditional GSA methods and it would be necessary to recondition the model to avoid correlation, or to apply more sophisticated GSA methods.

7.2.6 Fleet dynamics models

The effort share was identified as the most important input factor. We are already collaborating in a research project to develop new statistical approaches to describe fleet short-term dynamics and to show the value added of using more realistic models in the evaluation of fishery management strategies. Additionally, the era of big data, the recent availability of vessel monitoring system data and other electronic monitoring systems open a new window in the field of fleet dynamics modelling. Statistical analysis of this data could provide new insights on fleet dynamics, in relation to the spatio-temporal dimension, availability of stocks or environmental variables, for example. As the effort share was estimated to be the most important input factor in the application of the model, any improvement in the conditioning of fleet short-term dynamics will have a direct impact on the reliability of the results obtained.

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Appendix A

Nomenclature

AEE mean absolute value of the elementary effect.

AEE_p absolute elementary effect of trajectory p.

a age.

a_+ plusgroup age.

a_0 age at recruitment.

$ass.season$ assessment season.

A, B *sample* and *re-sample* matrices used to compute the importance indices in the Sobol method.

A_k^B matrix that is equal to A except in the column(s) that correspond with the k-th input factor which is (are) taken from matrix B.

$A_{i.}, B_{i.}, A_{k,i.}^B$ i-th row in the corresponding matrix.

B_{lim} limit biomass reference point in the precautionary approach framework.

B_{msy} biomass at MSY reference point used in the HCR proposed by Froese et al. (2011).

$B_{trig1}, B_{trig2}, B_{trig3}$ trigger biomass reference points used in an specific harvest control rule.

$B_{trigger}$ trigger biomass reference point used in the ICES harvest control rule.

BER break even revenue.

C catch in numbers or biomass.

C_{tg} target catch reference point in (Little et al. 2011).

CaC capital cost.

CB catch in weight.

CN catch in number of individuals.

cov covariate.

CrC crew cost.

CV coefficient of variation.

D discards in numbers or biomass.

DB discards in biomass.

DN discards in numbers.

E effort.

E_0 an effort threshold.

$E_{\max}$ maximum annual effort.

$\mathbb{F}$ set of all the input factors.

$\mathbb{F}_r$ set of input the factors selected with morris method when r trajectories are used.

$\mathbb{F}_{\mathrm{boot}_i}$ set of the input factors selected with the *calibrated visual* criterion in the i-th iteration of the boostrap.

$\mathbb{F}_{\mathrm{D}}$ set of the input factors selected with the *factors distinguished from the others* criterion.

$\mathbb{F}_{\mathrm{F}}$ set of the input factors selected using the *fixed-number of factors* criterion.

$\mathbb{F}_{\mathrm{H}}$ set of the input factors selected with the *factors with high AEE value* criterion.

$\mathbb{F}_{\mathrm{V}}$ set of the input factors selected with the *visual* procedure.

$\mathbb{F}_{\mathrm{W}}$ set of the input factors selected with the *weighted* criterion.

$\mathbb{F}_{conv}(N_t)$ set of the input factors that have converged with N_t sample size, and not with N_{t-1}, in the application of the Sobol method.

$\mathbb{F}_{r_{\max}}$ set of the input factors selected with morris method when $r_{\max}$ trajectories are used.

F fishing mortality.

F_{low} fishing mortality rate lower than Fmsy that produces a yield at equilibrium at most 5% lower than the yield produced by F_{msy}.

F_{max} fishing mortality rate that maximizes equilibrium yield per recruit.

F_{msy} fishing mortality rate that maximizes equilibrium yield.

F_{spwn} proportion of fishing mortality before spawning.

F_{upp} fishing mortality rate higher than Fmsy that produces a yield at equilibrium at most 5% lower than the yield produced by F_{msy}.

fec fecundity.

fl fleet.

FuC fuel cost.

FxC fixed Cost.

FxS fixed part of the salaries.

$\mathbb{F}_{\mathrm{M}}$ set of the input factors selected when the selection and convergence criteria are applied for the Morris method.

$\mathbb{G}_T$ set of total generalized indices.

G_{T_k} *generalized total-effect* index of the k-th input factor.

GV gross value.

h iteration.

i generic subscript used along the manuscript.

I_{lim}, I_{tg} target and limit reference point in abundance index used in the HCR tested in Little et al. (2011).

id abundance index.

Inv annual investment, given as a proportion of total revenue.

Inv_{max} the threshold (maximum) in annual investment, given as a proportion of total revenue.

J the dimension of the output of the simulation model.

j subscript used to refer to output variables.

K number of effective input factors in the application the Sobol or the Morris methods.

k subscript used to refer to k-th input factor.

K_p, K_i, K_d control parameters used in the HCR tested in (Pomarede et al. 2010).

K_r cardinality of $\mathbb{F}_r$.

$K_{\mathrm{EE},Z}$ number of input factors selected with the fixed number criterion when Z input factors are selected for each output variable.

K_{EE} number of input factors chosen *a priori* to be selected with the Morris method to be considered in the Sobol method.

K_{NG} number of input factors, without grouping, in the Sobol method.

$K_{r_{\max}}$ cardinality of $\mathbb{F}_{r_{\max}}$.

L landings in numbers or biomass.

l generic subscript.

LB landings in biomass.

LB_0 base landings in the price formation model.

LN landings in number of individuals.

M natural mortality.

m_X^r number of iterations in which a input factor X is selected in the bootstrap of the Morris method with r trajectories.

M_{spwn} proportion of natural mortality before spawning.

mat sample mean of maturity.

MSY maximum sustainable yield reference point.

mt subscript used to denote metiers.

N base sample size in the Sobol method.

n_a number of age classes.

n_u number of units.

n_y number of years in the simulation.

N_{boot} number of bootstrap iterations.

n_{cov} number of covariates.

n_{fl} number of fleets.

$n_{id,st}$ number of indices per stock.

$n_{mt,fl}$ number of metiers in fleet fl.

n_{mt} number of metiers.

n_{ss} number of seasons.

n_{st} number of stocks.

n_V number of vessels.

$\mathbb{P}$ a large enough set of trajectories defined in ω.

$\mathbb{P}_r$ the r trajectories within $\mathbb{P}$ that provide the best coverage of ω.

P population abundance in numbers at age or biomass.

p a trajectory in ω that belongs to $\mathbb{P}$.

PB population abundance in biomass.

PB_0 carrying capacity of a population.

PN population abundance in numbers at age.

PR price.

PR_0 base price.

PRF profits.

q catchability.

QS quota share.

R the cardinality of $\mathbb{P}$.

r the number of trajectories used in the Morris method.

r_{max} maximum number of trajectories used in the Morris method.

ret retention.

RP reproductive potential.

$\mathbb{S}_T^j$ the set of *total-effects* of output variable Y_j.

s number of parameters in the vectors at age model.

S_k *first-order* index for the k-th input factor.

S_{T_k} *total-effect* index for the k-th input factor.

$S_{T_k}^j$ *total-effect* index for the k-th input factor and output variable Y_j.

ss season.

ss_{spwn} spawning season.

st stock.

T set of benchmark iterations in the application of the Sobol variance decomposition method, such that $N_t < N$ for $N_t \in T$.

t elements in T.

TAC_{max}, TAC_{min} the maximum and minimum possible TAC in and specific HCR.

u seasonal cohort.

V variance.

VaC variable Cost.

w individual weight.

w_{D} the weight given to the *factors distinguished from the others* criterion in the computation of the calibrated visual criterion.

w_{F} the weight given to the *fixed-number of factors* criterion in the computation of the calibrated visual criterion.

w_{H} the weight given to the *factors with high AEE value.* criterion in the computation of the calibrated visual criterion.

$\boldsymbol{X_{\sim k}}$ multivariate input factor in Ω conditioned in all the input factors except the k-th one.

$\boldsymbol{X}$ multivariate input factor in Ω.

X an unidimensional input factor.

X_k k-th input factor.

$\boldsymbol{Y}$ a multidimensional output variable.

Y an unidimensional output variable.

y year.

y_0 first year of simulation.

Y_j j-th output variable.

y_{n_y} last year of simulation.

Z number of input factors selected for each indicator in the application of fixed-number of factors in the evaluation of the performance of the selection indicators.

α_1, α_2 the parameters of the Cobb-Douglass production function.

β elasticity parameter in the price function.

γ_i proportion of effort performed in metier i.

$\gamma_{\max}^{fl,mt}, \gamma_{\min}^{fl,mt}$ maximum and minimum limit for the proportion of effort exerted by the fleet fl in metier mt.

Δ width of the subintervals in the Morris method.

δ_{D} proportion used in the *factors distinguished from the others* criterion to select those input factors that are aside of the rest.

δ_{F} number of input factors selected in the *fixed-number of factors* selection criterion.

δ_{H} proportion used in the *factors with high AEE value* selection criterion.

ϵ residuals in vectors at age models.

ε observation error.

ζ perception bias in the management procedure.

η_0, η_1, η_2 parameters in the capital function.

Θ first performance indicator.

Θ_G generalized performance indicator.

θ parameters in the vectors at age models.

ϑ threshold for the maximum proportion of catch that can be caught from a stock.

ι_1, ι_2 parameters in Pella-Tomlinson population growth model.

κ fleet's capacity.

Λ matrix of aging errors, element (ij) represents the proportion of individuals of age i assigned to age j.

λ the elements in matrix Λ.

μ mean value of the observable variables in the operating model.

ν	threshold used for proportion to select the important input factors in the bootstrap of the Morris methods.
χ_{MP}	variable in the management procedure that comes from an observation in the operating model.
χ_{OM}	variable in the operating model.
$\vec{\chi}$	a vector with values at age of a given input factor.
Ξ	set of stocks for which the catch constraint must be fulfilled in the profit maximization function.
ξ	natural variability in the operating model.
π^r_X	indicates whether X has been selected in the iterations a bootstrap of the Morris method with r trajectories.
ρ^j_k	auxiliar variable used to calculate the performance indicators, Θ and Θ_G, in the evaluation of the selection criteria corresponding to the k-th input factor and the j-th output variable.
ϱ_1, ϱ_2	parameters of the beta distribution used to condition maturity ogives.
τ_i	parameters in the HCRs.
Υ	variation in capacity.
υ_a, υ_i	parameters of the Dirichlet distribution in aging error.
ϕ_{pop}	population growth model.
ϕ_{rec}	stock-recruitment model.
$\varPhi$	model to describe vectors at age
ψ_1, ψ_2	parameters of the stock-recruitment model.
φ	simulation model.
φ_i	elements in the high dimensional model representation.
Γ	fleet's landings or total landing in the fishery.
Ω	existence domain of the simulation model.
ω	$[0,1]^K$ unit hypercube.

Appendix B

List of input factors

Table B.1: All the random factors considered in the GSA. They are ordered in alphabetical order. The name column correspond with the name used to denote the factors in the figures and the tables. The other three columns correspond with the component of the model the factor belong to, its description and the stock and/or fleet it belong to.

Name	Component	Description	Stock/Fleet
AgingError_HKE AgingError_HOM AgingError_LDB AgingError_MEG AgingError_MON	Observation Model	Error in the aging process. The probability of assigning age 'i' to a fish of age 'j'	Hake H.Mackerel 4 Spot M. Megrim Monkfish
CapitalCost_DFN_SP CapitalCost_DTS_SP CapitalCost_HOK_SP	Fleets OM Entry-Exit Model	Current value of the capital invested multiplied with the opportunity cost of capital	Gillnetters Trawlers Longliners
Crewshare_DFN Crewshare_DTS Crewshare_HOK	Fleets OM Entry-Exit Model	The proportion of the turnover that is paid to the crew	Gillnetters Trawlers Longliners
DiscNError_HKE DiscNError_LDB DiscNError_MEG	Observation Model	Error in the observed numbers of discarded fishes	Hake 4 Spot M. Megrim
DiscWError_HKE DiscWError_LDB DiscWError_MEG	Observation Model	Error in the observed total weight of discards	Hake 4 Spot M. Megrim
Effshare_DFN Effshare_DTS Effshare_HOK	Fleets OM Short Term Dynamics	Distribution of total effort among metiers	Gillnetters Trawlers Longliners
Fcost_DFN Fcost_DTS Fcost_HOK	Fleets OM Entry-Exit Model	Fixed Cost per vessel Also used to calculate profits at fleet level	Gillnetters Trawlers Longliners
FuelCost_DFN_SP FuelCost_DTS_SP FuelCost_HOK_SP	Fleets OM Entry-Exit Model	Fuel Cost per unit of effort	Gillnetters Trawlers Longliners
InvestShare	Fleets OM Entry- Exit Model	Proportion of profits used to invest in new vessels	Fleet independent
LandNError_HKE LandNError_HOM LandNError_LDB LandNError_MEG LandNError_MON	Observation Model	Error in the observed numbers of landed fishes	Hake H.Mackerel 4 Spot M. Megrim Monkfish
LandWtError_HKE LandWtError_HOM LandWtError_LDB LandWtError_MEG	Observation Model	Error in the observed total weight of landings	Hake H.Mackerel 4 Spot M. Megrim

LandWtError_MON			Monkfish
M_HKE M_HOM M_LDB M_MEG M_MON	Biological OM	Instantaneous rate of natural mortality at age	Hake H.Mackerel 4 Spot M. Megrim Monkfish
Mat_HKE Mat_HOM Mat_LDB Mat_MEG Mat_MON	Biological OM	Proportion of mature individuals at age	Hake H.Mackerel 4 Spot M. Megrim Monkfish
MaxDays_DFN_SP MaxDays_HOK_SP MaxDaysCost_DTS_SP	Fleets OM Entry-Exit Model	Maximum Number of Days a vessel can operate within a year	Gillnetters Trawlers Longliners
N_HO8 N_MAC N_WHB	Biological OM	Number of fish at age along the simulation	Western H. Mac. Mackerel Blue Whiting
N_HKE N_HOM N_LDB N_MEG N_MON	Biological OM	Number of fish at age in the first year of the simulation	Hake H.Mackerel 4 Spot M. Megrim Monkfish
price_HKE price_HOM_HO8 price_MAC price_MEG_LDB price_MON price_WHB	Fleets OM Entry-Exit Model	Fleet and Metier Independent Price of fish per ton	Hake Horse Mackerels Mackerel Megrims Monkfish Blue Whiting
price_OTH_DTS_SP_M1 price_OTH_DTS_SP_M2 price_OTH_DTS_SP_M3 price_OTH_HOK_DFN_M1 price_OTH_HOK_DFN_M2 price_OTH_HOK_DFN_M3 price_OTH_HOK_DFN_M4 price_OTH_HOK_DFN_M5 price_OTH_HOK_DFN_M6	Fleets OM Entry-Exit Model	Price per ton of the OTH stock. The composition of OTH depends on the metier and hence the price is metier dependent.	OTH Trawlers OTB_DEM OTH Trawlers OTB_PEL OTH Trawlers PTB OTH G&L Trammel net OTH G&L Hand Line OTH G&L Longine OTH G&L Gillnet ¿= 100 OTH G&L Gillnet 60-79 OTH G&L Gillnet 80-99
q_HKE_Baka_SP q_HKE_DTS_PT q_HKE_GNs_60 q_HKE_GNS_80 q_HKE_LLS q_HKE_Pair q_HKE_PGP_PT q_HO8 q_HOM _PS_PT q_HOM_DFN_HOK q_HOM_DTS_PT q_HOM_DTS_SP q_HOM_PGP_PT q_HOM_PS_SP q_LDB q_MAC q_MEG q_MON_DTS_PT q_MON_DTS_SP q_MON_HOK_DFN q_MON_PGP_PT q_OTH_DTS_SP_M1 q_OTH_DTS_SP_M2 q_OTH_DTS_SP_M3 q_OTH_HOK_DFN_M1 q_OTH_HOK_DFN_M2 q_OTH_HOK_DFN_M3 q_OTH_HOK_DFN_M4 q_OTH_HOK_DFN_M5 q_OTH_HOK_DFN_M6 q_WHB	Fleets OM Catch Production Model	Catchability per fish stock (Defined at metier/fleet level depending on data availability)	Hake SP Trawl Hake PT Trawl Hake G&L 60-79 Hake G&L 80-99 Hake G&L Longline Hake SP Trawl PTB Hake PT PGP W. Horse Mackerel H. Mackerel PT PS H. Mackerel G&L H. Mackerel PT Trawl H. Mackerel SP Trawl H. Mackerel PT PGP H. Mackerel SP PS 4 Spot Megrim Mackerel Megrim Monkfish PT Trawl Monkfish SP Trawl Monkfish Sp. G&L Monkfish PT PGP OTH Trawlers OTB_DEM OTH Trawlers OTB_PEL OTH Trawlers PTB OTH G&L Trammel net OTH G&L Hand Line OTH G&L Longine OTH G&L Gillnet ¿= 100 OTH G&L Gillnet 60-79 OTH G&L Gillnet 80-99 Blue Whiting
ret_HKE_DTS_SP ret_HKE_DTS_PT ret_LDB_DTS_SP ret_MEG_DTS_SP ret_MAC	Fleets OM Entry-Exit Model	The retention ogive. A vector at age with the proportion of catch that is retained onboard	Hake SP Trawl OTB Hake PT Trawl 4 Spot Megrim SP Trawl 5 Spot Megrim SP Trawl Mackerel all fleets
SR_params_HKE SR_params_HOM SR_params_LDB SR_params_MEG SR_params_MON	Biological OM Stock Recruitment Model	The parameters of the stock recruitment models	Hake H.Mackerel 4 Spot M. Megrim Monkfish
SR_uncerta_HKE SR_uncerta_HOM SR_uncerta_LDB SR_uncerta_MEG	Biological OM Stock Recruitment	A time series with the annual deviations of recruitment from stock-recruitment model	Hake H.Mackerel 4 Spot M. Megrim

SR_uncerta_MON	Model		Monkfish
StkNError_HKE StkNError_HOM StkNError_LDB StkNError_MEG StkNError_MON	Observation Model	A vector at age with the observation error in the stocks numbers	Hake H.Mackerel 4 Spot M. Megrim Monkfish
StkWError_HKE StkWError_HOM StkWError_LDB StkWError_MEG StkWError_MON	Observation Model	A vector at age with the observation error in the stocks weight	Hake H.Mackerel 4 Spot M. Megrim Monkfish
TAC_HO8 TAC_MAC TAC_WHB	Advice Model	The TAC of the widely distributed stocks	Western H. Mac. Mackerel Blue Whiting
vcost_DFN vcost_DTS vcost_HOK	Fleets OM Entry-Exit Model	Variable Cost per unit of effort	Western H. Mac. Mackerel Blue Whiting
w1 w2	Fleets OM Entry-Exit Model	Proportion in which capacity (in/de)crease (w1/w2) yearly	Fleet independent
Wt_HKE Wt_HOM Wt_LDB Wt_MEG Wt_MON	Biological OM Stock Recruitment Model	A vector at age with the mean weight of the fish individuals	Hake H.Mackerel 4 Spot M. Megrim Monkfish

Appendix C

Abbreviations

AEE mean absolute elementary effect.

CFP common fisheries policy.

CV coefficient of variation.

EC European Commission.

F fishing mortality.

FLR fisheries libraries in R.

GSA global sensitivity analysis.

GSI generalised sensitivity indices.

HCR harvest control rule.

ICES international council for the exploration of the sea.

MMP multi-annual management plan.

MP management procedure.

MSE management strategy evaluation.

MSY maximum sustainable yield.

NPV Net present value.

OM operating model.

SSB spawning stock biomass.

TAC total allowable catch.