A benchmark of stock assessment models for *Octopus vulgaris* in Portugal

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“ Bom... vamos lá ver... eu só estou aqui para ajudar. ”

Pedro da Conceição, imbubido do espírito de missão

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Abstract

Faculdade de Ciências da Universidade do Porto
Departamento de Ciência de Computadores

MSc. Data Science

A benchmark of stock assessment models for *Octopus vulgaris* in Portugal

by Alberto ROCHA

Cephalopod fisheries have historically presented unique obstacles in their assessment, due to the short lives and single spawning cycle that are characteristic of the species in this *taxa*. Common Octopus, *Octopus vulgaris*, is the most important cephalopod fishery in Portugal and as such, there is a demand for both stock assessment approaches and tools to better assist in the management of the fishery. This work aims to compare the performance of some of the available approaches for stock assessment data for the Octopus fishery in both their ability to adequately describe the stock dynamics and to be integrated in tools that can be deployed to provided actionable information to the decision makers.

Keywords: Fisheries, stock assessment, *Octopus vulgaris*, common octopus, surplus production models, depletion models, *CMSY++*, *JABBA*, *SPiCT*, *CatDyn*

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Resumo

Faculdade de Ciências da Universidade do Porto
Departamento de Ciência de Computadores

Mestrado em Ciências de Dados

Uma revisão de vários métodos de avaliação de *stocks* para o polvo vulgar em Portugal

por Alberto ROCHA

As pescarias de cefalópodes são consideradas de difícil avaliação devido a algumas características intrínsecas a este grupo taxonómico tais como ciclo de vida curto e um único momento de reprodução. A pescaria do polvo comum, *O. vulgaris*, é a pescaria de cefalópodes mais importante em Portugal dos pontos de vista social e económico, pelo que existe amplo interesse em ferramentas de gestão que possam apoiar esta pescaria. Este trabalho visa comparar o desempenho de várias abordagens à avaliação dos dados da pescaria de polvo em Portugal, quer do ponto de vista da qualidade da avaliação da dinâmica e estado do *stock* quer da viabilidade da integração da metodologia em ferramentas de suporte à decisão.

Palavras-Chave: Pescas, avaliação de *stock*, *Octopus vulgaris*, polvo-vulgar, modelos de produção, modelos de depleção, *CMSY++*, *JABBA*, *SPiCT*, *CatDyn*

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Symbols

α	Non-linear effect on effort
β	Non-linear effect on abundance
χ_t	(GDM) Observed catch at time t
B	Biomass
B_0	Biomass at start of exploitation
B_{t+1}	Stock biomass of the year $t+1$
B_t	Stock biomass at the beginning of the year t
B_{MSY}	Biomass that would produce the MSY
C_t	Biomass caught in the year t
$CPUE$	Catch per unit of effort
E	Effort
E_{MSY}	Maximum sustainable effort
F_t	Instantaneous coefficient of fishing mortality
F_{MSY}	F that would produce the MSY
$f(B_t)$	Function of surplus biomass production
I_t	Standardized index of relative biomass
I	(GDM) Indicator variable for signaling perturbation events
J	(GDM) Indicator variable for signaling perturbation events
R	Recruitment magnitude
K	(SPM) Carrying capacity of the stock
k	(GDM) Scaling factor of the catch function

$LPUE$	Landing per unit of effort
MSY	Maximum Sustainable Yield
m	Alternative formulation for the shape parameter of the production curve in a SPM
N_0	Initial population at the beginning of the season
N_t	Population at time t
p	Shape parameter of the production curve in a SPM
P	Biomass relative to carrying capacity
P_{lim}	P threshold under which recruitment is impaired
q	Catchability coefficient
r	Intrinsic rate of population natural increase
R	Recruitment magnitude
S	Female spawner magnitude

Glossary

ACF	Autocorrelation Function
ADF	Augmented Dickey-Fuller test
AIC	Akaike Information Criterion
$ASPIC$	A Stock-Production Model Incorporating Covariates
BSM	Bayesian surplus model
BSP	Bayesian Surplus Production stock assessment software
$CatDyn$	Catch Dynamics instead of fish Population Dynamics
$CCMAR$	*Centro de Ciências do Mar, Universidade do Algarve*
$CEDA$	Catch Effort Data Analysis package
CFP	Common Fisheries Policy
$cilow$	Lower confidence interval
$ciupp$	Upper confidence interval
CL	Confidence Level
$CPUE$	Catch-per-unit-effort
$CMSY$	Catch-only estimation method
$CMSY++$	Advanced state-space Baysiean method for stock assessment
DCF	Data Collection Framework
$DGAM$	*Direção-Geral da Autoridade Marítima*
$DGRM$	*Direcção-Geral de Recursos Naturais, Segurança e Serviços Marítimos*
$DOPESCA$	*Docapesca – Portos e Lotas, S.A.*
EU	European Union

ICES	International Council for the Exploration of the seas
ICNF	*Instituto da Conservação da Natureza e das Florestas*
INE	*Instituto Nacional de Estatística*
IPMA	*Instituto Português do Mar e da Atmosfera*
FAO	Food and Agriculture Organization
FishStat	Fisheries statistics and information from FAO
GSA	Geographical Sub-Areas
GDM	Generalized Depletion Model
GLM	Generalized Linear Model
GFCM	General Fisheries Commission for the Mediterranean
JABBA	Just Another Bayesian Biomass Assessment
JAGS	Just Another Gibbs Sampler
KPSS	Kwiatkowski-Phillips-Schmidt-Shin test
Kobeplot	Assemblage of a phase plot and a strategy matrix
LaTeX	System for high-quality technical typesetting - TeX macro language
lci	Lower confidence interval
LPUE	Landing-per-unit-effort
log.est	Logarithmic estimate
kW	Engine power units in Kilowatt
MIS	Mixture of artisanal fishing gears used by small-scale fisheries
MSC	Marine Stewardship Council
MSQUID	GDM-based stock assessment package
NGOs	Non-governmental organizations
pACF	Partial autocorrelation Function
$PONG - Pesca$	*Plataforma de ONG Portuguesas sobre a Pesca*
OCC	3-letter FAO code for *Octopus vulgaris*
OCT	3-letter FAO code for *Octopus* spp.

OTB	Otter Bottom trawlers
PS	Purse Seiners
R	Language and environment for statistical computing and graphics
RSTUDIO	Integrated development environment for R language
Shiny	R package, that builds interactive web applications
SPiCT	Stochastic surplus Production model In Continuous Time
SPM	Surplus Production Model
uci	Upper confidence interval
WWF	World Wildlife Fund
WGCEPH	Working Group on Cephalopod Fisheries and Life History

Ao Alberto Rocha anterior.

Chapter 1

Introduction

The fisheries and aquaculture sectors have been increasingly recognized for their essential contribution to global food security and nutrition in the twenty-first century [1]. A correct management of fisheries is of utmost importance and a key component of such management is the ability to assess the status of the fish stock. Stock assessment provides the necessary insight to gauge whether a given exploitation rate of the stock is sustainable or, when it is not, an estimate to the necessary correction in fishing effort and mortality.

As a practical problem, fish stock assessment presents significant challenges. Some approaches such as spawning biomass-recruitment relationship, surplus production or depletion models have become the basis of most models that are developed for stock assessment [2]. In practice, each local fishery presents a unique challenge that has to be tackled individually, with the more general models having to be adapted to the observations and dynamics unique to that fish stock. Whether the best approach will require accommodating information on, for example recruitment pulses, seasonal changes in fishing operations, short-term or long term migrations, one or more spawning seasons, is exceedingly hard to gauge *a priori*. A one-size-fits-all tool that provides a statistical framework that can accommodate such a work would be at best, extremely impractical and incomplete and, at worst, a pipe dream. Most of the work is typically done in general-purpose mathematical frameworks such as *R* [3], *Python* [4] or *MatLab* [5], with the support of highly specialized libraries [6]. This results in most analysis being performed in extremely personalized and complex (often borderline inscrutable) scripts, which presents an obstacle for the divulgation and reproducibility of the methodologies developed. Some tools have been developed that achieve a compromise, allowing fishery biologists to implement commonly used stock assessment models without having to implement every routine from the ground up while allowing some flexibility in their use.

This works examines some examples of such tools, specifically those developed for *R*. They are distributed as *R* packages, with one notable exception. Using the common octopus fishery in Portugal, the different tools are compared, both in their ability to provide a meaningful assessment of the fishery and their ability to be integrated in other tools, such as dashboards or wrappers that would allow less experienced users to interact with the models.

1.1 Structure of this dissertation

The background for this work is presented in the first chapter. Some key facts of the life history and biology of the species in focus, *Octopus vulgaris* are presented. We present a brief summary of the status of octopus fisheries and their management. Some approaches to stock assessment for cephalopods fisheries are discussed and two relevant statistical frameworks are presented in greater detail: Surplus Production Models and Generalized Depletion Models. Four methodologies for stock assessment based in these approaches are also presented: *CMSY++*, *JABBA*, *SPiCT* and *CatDyn*.

The second chapter describes the methodology followed throughout this work. Data sources are presented and the rationale behind data processing steps taken is discussed. The implementation of each method is then discussed, with the differences required by each approach being highlighted. The approach to evaluating the performance and adaptability of each method is also discussed at this stage.

Results are presented on the third chapter, beginning with an exploration of the dataset used. Trends in the time series of landings and effort are described. Results for each method are then provided, both in terms of plausability of stock assessment estimates and in terms of performance and usability.

In the fourth chapter results are discussed, with the focus being in the relationship of the observed discrepancies between the methods assessed and the expectations each form of implementation may create on the user. Ideas towards improving a framework for assessing the octopus fishery in a realistic setting are also discussed. Conclusions for this work are summarised in the final chapter.

1.2 Aims of this work

The goals of this work were:

- Apply the *CMSY++*, *JABBA*, *SPiCT* and *CatDyn* stock assessment methods to data on the Portuguese octopus fishery;
- Identify limitations and differences on the application each method;
- Assess how each method is suited to be used in a general public facing tool such as an app;
- Build a *Shiny* app prototype to test the integration of each method in such a tool.

The following section will introduce the background for this work, regarding the octopus fishery in Portugal, the statistical frameworks and stock assessment models examined in this work.

Chapter 2

Background

In this section, life history and biology, status of the fisheries and management approaches for *Octopus vulgaris* are presented. Two of the statistical frameworks on which most cephalopod stock assessment methods are based are presented: Surplus Production Models and Generalized Depletion Models. Four methodologies for stock assessment based in these approaches which will be examined in this work are also described in detail.

2.1 *Octopus vulgaris*

The common octopus *Octopus vulgaris* (Cuvier, 1797) is a mollusc from the class *Cephalopoda* (order: *Octopoda*; family: *Octopodidae*). It is a neritic benthic species, tipically found in temperate shallow habitats ranging from the coastline up to 200m depths [7], favouring rocky grounds, coral reefs and grass beds [8]. Currently, the species names *Octopus vulgaris* is considered a species complex that encompasses both *Octopus vulgaris sensu strictu* and at least 4 additional *taxa* that are designated as *Octopus vulgaris* type I to IV [7]. Their distributions are disjunct and cover Europe, Asia, Africa and America (Figure 2.1). The portuguese octopus fishery targets *Octopus vulgaris sensu strictu* ranges from the Northwest coast of Africa, the Mediterranean Sea and the European coast up to the Baltic Sea.

As all cephalopods, the common octopus are dioecious, with external sexual dimorphism. For this species, this consists in the presence of a modified arm (the hectocotylus) capable of transferring spermatophores from male to the mantle cavity of females. Octopus are semelparous, with the male becoming senescent and dying shortly after fecundation. Females typically deposit the eggs in a den and care for them until hatching, dying shortly after [9]. This phenomenon is attributed to a hormonal mechanism triggered by reproduction that suppresses the feeding instinct [10]. Thus, typical lifespan for octopus has been observed to range between 12 and 18 months [11].

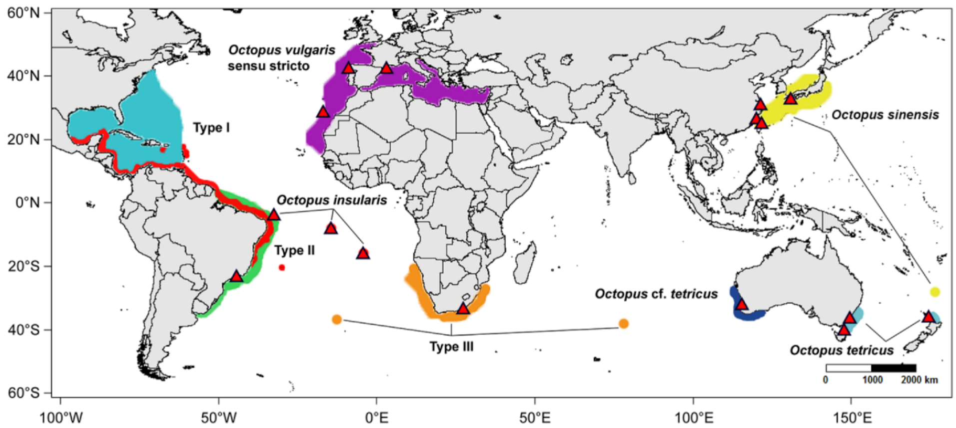


FIGURE 2.1: Global distribution of octopus [12].

Spawning season for octopus typically extended throughout the year, though depending on location, one or more spawning peaks may be observed. In Portuguese waters, spawning peaks have been observed in April and August in the northern shelf, whereas in the southern shelf a shorter spawning season occurs throughout the summer [13]. Octopus are estimated to reach the minimum size for fishery (in Portugal, a weight of 750g [14]) at 9 to 10 months old [15].

2.2 Octopus fisheries

Octopus fisheries worlwide

Evidence for the existence of octopus fisheries can be traced back to ancient times, with explicit mentions being found in ancient Greek and Roman literature [16]. Written records in the modern era can be reliably obtained from 1950 onwards [16] and landing statistics are currently compiled by the Food and Agriculture Organization *FAO* and available on *FishStat*[17]. Several species from the order *Octopoda* can be included in official catch reports (Amor et al. 2017; Gleadall 2016a in [16]), so accurate figures for *Octopus vulgaris* on a global scale are difficult to obtain. The data from *FishStat* [17] shows that globally octopus fisheries are a positive trend, with the exception of landings from Europe which are on a steady decline (Figure 2.2). China is the largest producer, with countries like Morocco, Mexico and Mauritania following. The largest importers, as of 2020, were the Republic of Korea, Spain and Japan [18].

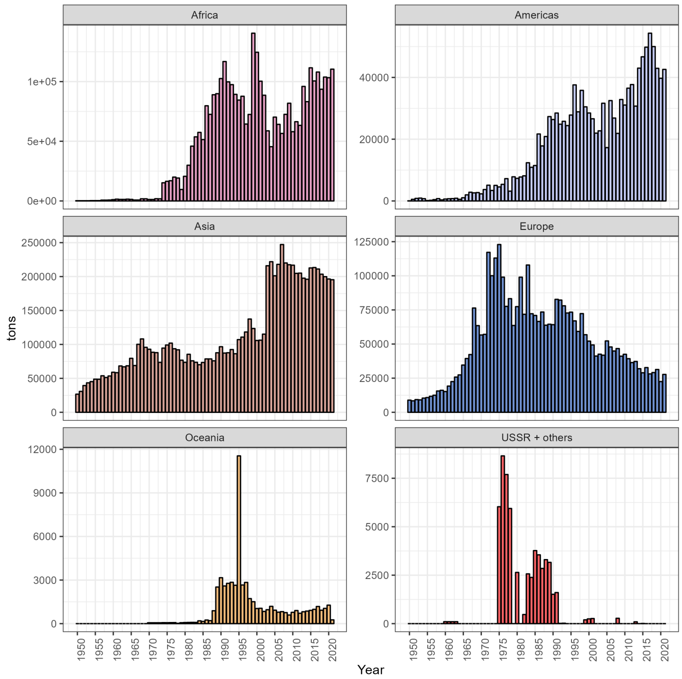


FIGURE 2.2: Estimated landings of octopus worldwide (source: *FAO*) ([17]). Some countries were either unidentified or assigned a generic 'USSR' descriptor in the dataset.

Data concerning landings reported specifically as *Octopus vulgaris* is also available on *FishStat* (Figure 2.3), for that restriction is worth.

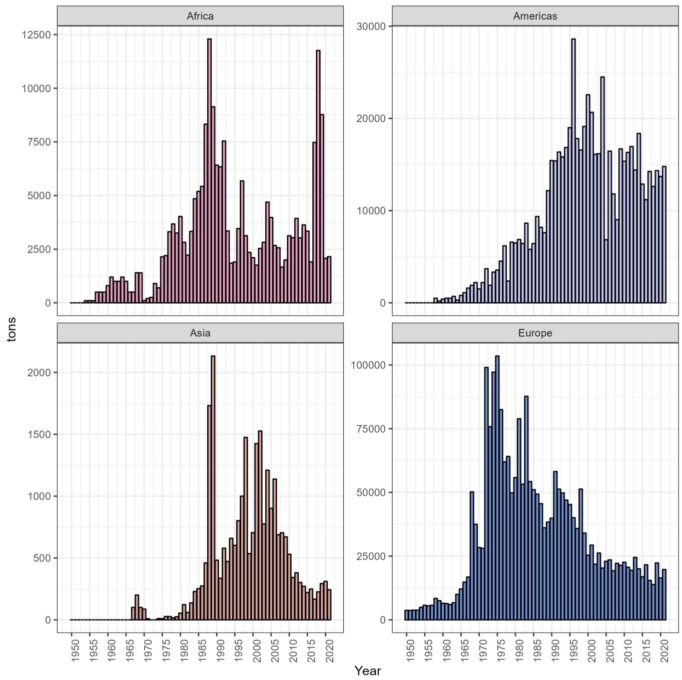


FIGURE 2.3: Estimated landings reported as *Octopus vulgaris* worldwide (source: FAO) [19].

Reportedly, *O. vulgaris* landings are higher in European and American countries, though global landings have been on a decline on recent decades, a trend that is driven by the steep decline in European results.

Octopus fisheries in Portugal

Octopus is one of the most valuable commercial catches in Portuguese fisheries and a preferential target for many small-scale fisheries [20]. The majority of octopus landings occur in pots and traps fisheries set by small vessels operating close to the shore [21, 22]. Fisheries that target octopus are mostly grouped with other small-scale fisheries in the polyvalent segment of the fishing fleet, in opposition to the purse-seine and bottom-trawl segments [22]. According to the *Instituto Nacional de Estatística* (INE) [23], octopus landings in Portugal oscillate between 5000 and 10000 tons/year, with some years such as 2008 and 2013 reaching as high as 15000 tons (Figure 2.4). Octopus constitutes a significant portion (between 4 and 10%) of all fishery products landed, and accounts for between 11 and 19% of the total revenue on first sale of fishery products by the fishing fleet (figure 2.4) and small-scale fisheries such as those which target Octopus feature a high economical value and socioeconomic importance despite the comparatively small number of professionals involved in them [20, 21, 24].

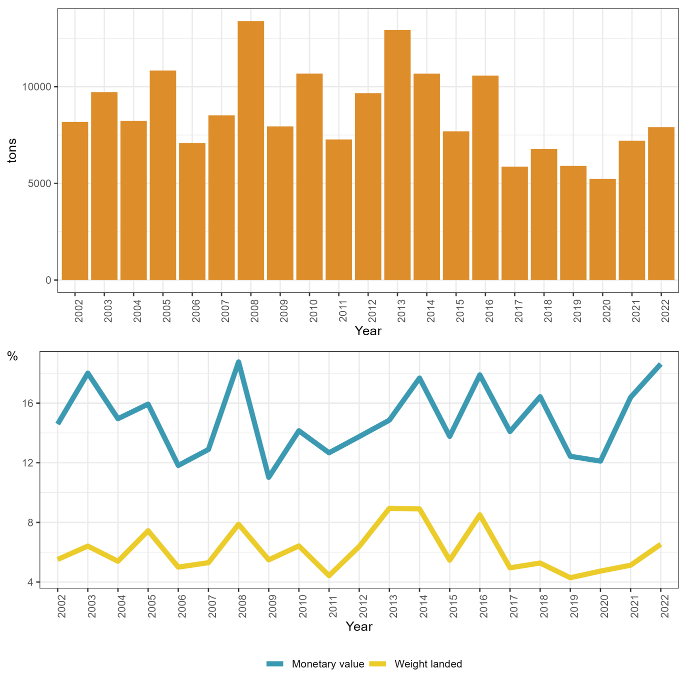


FIGURE 2.4: Octopus landings (tons) by the fishing fleet in Portugal (top) and contribution of octopus towards the first sale revenue and the total landings, in percentage (down), in the period of 2002-2022. Source: *INE* [23].

Among the fishing gears traditionally used to target octopus, the most predominant are:

- Traps - Octopus fishing traps are framed with a single entrance partially blocked (usually by plastic strips), easy to push in by an octopus but not back out. These traps are of different sizes and can be baited inside with fish, being forbidden to baited with live crabs in Portugal [25]. Traps can be made with materials such as wood, wicker, metal rods, wire netting, plastic among others, built into either a framed structure or a more simplistic pot configuration [26–28]. They can be deployed either individually or, most commonly, in groups of several dozens or even hundreds connected by a long line ('caça') which is then handled with pot haulers or line coilers [26, 27]. Soaking time can range from a couple of hours to several days.

- Bottom-trawl fishery - The gear consists on a large mesh net dragged by cables from a vessel. The horizontal spread of the net over the sea bottom is provided by two bottom or universal trawl doors (also known as otter boards), which settle the net on the substrate. In Portugal, bottom trawlers mostly do not target octopus and such catches are considered bycatch [22]. A subset of the fleet has been observed to engage in the fishery sporadically, taking advantage of seasonal spikes in abundance [29]. Worldwide, there are bottom trawler fleets that exclusively target octopus, such as the fishery in the Saharan Bank, NW Africa [16].

- Other fishing gears, such as purse seiners and trammel nets, can report octopus landings, although only as very occasional bycatch. Purse seines operate encircling fish schools in mid-water, close to the surface, by a netting wall with small meshes. The lower part of the net is then closed to prevent escapement by diving [27]. Trammel nets are stationary nets with three layers of netting to usually entangle demersal fishes and crustaceans, kept vertical by floats on the headrope and weights on the footrope [16].

2.3 Fisheries management for Octopus

Under the Common Fisheries Policy (*CFP*), cephalopod fisheries using traps in the European Union are excluded from quota regulations, with management falling under national or local jurisdiction [30]. Despite some cephalopod fisheries being successfully managed in places such as Argentina, Australia, Canada, Chile, Falkland Islands, Japan, Mexico, New Zealand, Peru, Russia, and South Africa, many important cephalopod fisheries in other parts of the world are currently not assessed or managed [31].

In Asturias (Spain), a co-management approach has been in place since 2001. Such an approach allows the stakeholders (fishers, distributors) and governing bodies to participate in the management of the fishery [20, 32]. Since 2016, this fishery also became the first octopus fishery to be certified by the Marine Stewardship Council (*MSC*), which has been linked to an increased valuation of Asturian octopus [33]. Since then, only the Western Australia octopus fishery has been granted the Blue *MSC* Label certification, in 2019 [34]. In order to maintain such a certification, evidence of sustainability must be provided, which often requires stock assessment to be performed.

For octopus stocks such as those in Portugal, Spain, Italy or Greece, a formal assessment has not yet be implemented, so management is based in technical measures targeting input and output control, such as limitations on number of traps/pots, restrictions on fishing days, fishing seasons, gear design, among others [20].

In Portugal, there is currently a participatory co-management plan being implemented for the Algarve octopus fishery. Among this, the goals included improvements in monitorization, assessment and protection of the fishery. The comittee includes representatives from the fishing sector (fisher associations and other stakeholders), administration (*DGAM*, *DGRM*, *DOCAPESCA*, *ICNF*, among others), scientific research (*IPMA*, *CCMAR*) and non-governmental organizations (*NGO*s) such as *PONG-Pesca* and *WWF*. The current target for a fully co-managed fishery is 2035 [35], but short term goals are in place which include a preliminary assessment of the fishery and the regulation of fishing effort through the establishment of an annual closed season in this fishery [36].

Presently, some management measures are used to either target or affect the octopus fishery in Portugal. For example, limitations on the number of licenses allowed, number of traps per vessel and restrictions on gear design are regulated. There is a prohibition on the usage of live bait in traps and a limit on the distance the traps can be set from the coast. There is a minimum landing weight of 750g [37]. Capture and sales of octopus on the weekends have been intermittently prohibited in Algarve [38].

Portuguese octopus fisheries occur in areas under the International Council for the Exploration of the seas (ICES), specifically in statistical area IXa (Figure 2.5). Under *ICES*, the Working Group on Cephalopod Fisheries and Life History (*WGCEPH*) compiles data on octopus landing and fishing effort from *ICES* member countries and actively reports its work on monitoring of fishery trends, production of catch-per-unit-effort (CPUE) data series, developing approaches for cephalopods stock assessment, understanding of the dynamics of fleets targeting cephalopods, and evaluation of Data Collection Framework (DCF) effectiveness in sampling [22]. While no formal advice is given for stock managament, stock status assessment is trend-based, with the average landings from the last 3-years period being compared to the historical mean [22].

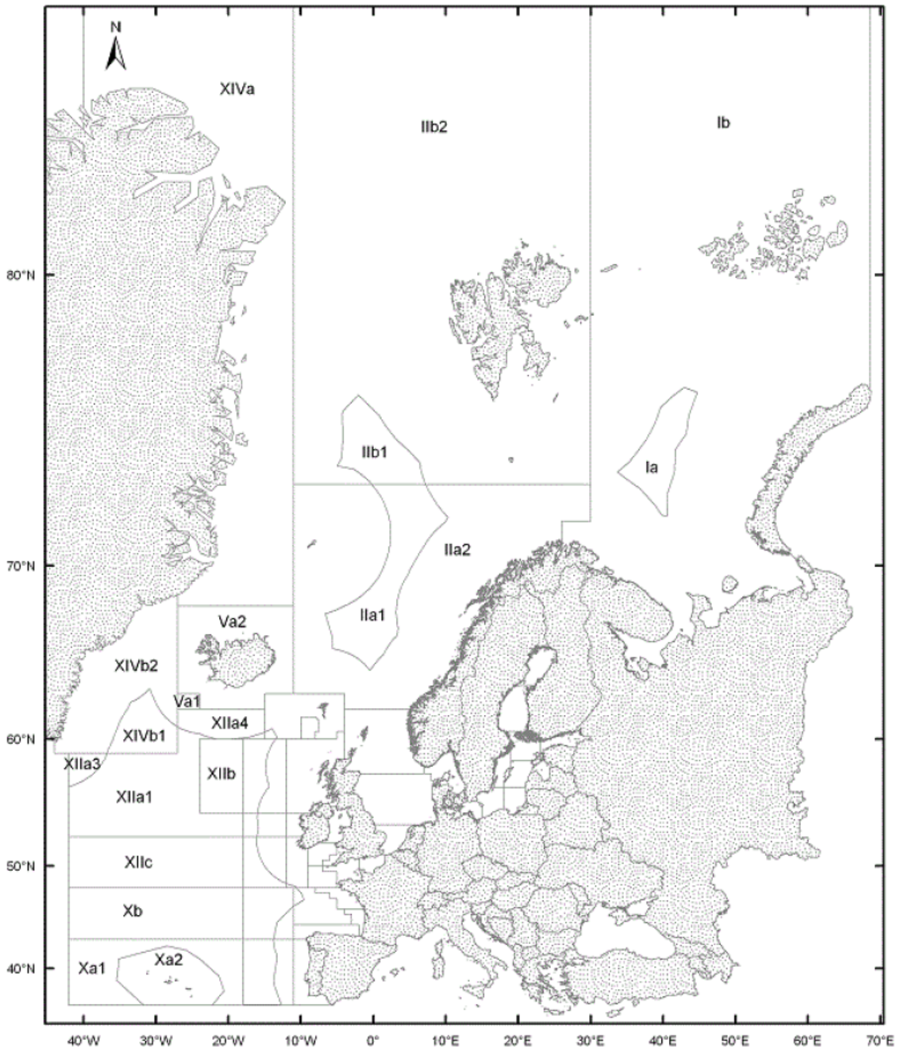


FIGURE 2.5: Statistical areas under the jurisdiction of the International Council for the Exploration of the Seas (ICES) [39].

2.4 Stock assessment for Octopus

The main goal of stock assessment is to provide fishery stakeholders and decision-makers with information on the stock status, in order to ensure that stock biomass is kept on a sustainable level and fishing mortality does not exceed the stock capacity to regenerate itself. Such capacity is evaluated typically by estimating biological reference points based on which thresholds can be established [40]. The majority of stock assessment models have been traditionally developed for long-lived fish species or invertebrates and therefore are not really well suited for the short-lived cephalopod species [40]. The main specificities for cephalopods, as far as assessment is concerned, include:

- Short life cycles: The lifespan of most cephalopods ranges between 6 months and 2 years, with most species living on average 1 year. Data collection for these species typically requires high granularity and short timescales. Models that rely on constant natural mortality values throughout the entire series (typically, several years) or well defined age structure in the population are ill-suited for these species.

- Scarcity of age data: Age data for fish can be reasonably estimated with yearly increments of calcified deposits in their inner ear, known as otoliths. On most species these structures are easily collectable and age estimation, in years, can be performed reliably [41]. On cephalopods, calcified structures known as statoliths [42] are also available which also can be used for age estimation, but their collection, processing, and interpretation is typically orders of magnitude more complex and time-consuming than their fish-counterparts. While they have been used with success for some cephalopod species, mixed results with octopus have led to the search of alternatives [41, 43] such as increment analysis of beaks and stylets [41, 44].

- Complex population structure: Along with their shorter life spans, many cephalopod species either have several spawning peaks throughout the year or, in alternative, have protracted, year-round spawning. This results in populations having several microcohorts per year, instead of a singular yearly cohort. The complexity in populations structure due to a protracted spawning season is more intense in upwelling areas such as the Portuguese coast characterized by a long high productivity season and relatively low variations in the favourable enviromental conditions for reproduction [13, 45]. Models that rely on tracking cohorts throughout the time series are therefore inadvisable for cephalopods [40].

- Rapid growth rates: Despite following allometric growth, cephalopods have very high growth rates, reaching remarkable sizes in their short lifespans. Growth rates are very dependent on environmental and ecological factors and often display very high inter annual variability [40].

- Data limited fisheries: Many cephalopods (including *O. vulgaris*) are mostly caught in small-scale fisheries. Monitoring these fisheries often raises additional issues regarding data collection since most vessels who engage in these fisheries are either exempt from or unwilling to comply with restrictions and regulations that assist in data collection. Effort data, information on gear used, logbooks, positional data of the fishery are some of the data that becomes harder to obtain in small-scale fisheries [40].

2.5 Methods considered in this work

ICES defines 6 categories for the assessment of a stock, based on the availability of data and the scope of the assessment that is possible [46]:

- Category 1 - Full analytical assessments and forecasts are possible.
- Category 2 - Analytical assessments possible, but forecasts treated qualitatively (as trends).
- Category 3 - Data on how fish abundance and/or biomass has changed over time (mostly from research vessel surveys) is used to provide advice.
- Category 4 - Advice is given on the bases of specialised modelling methods that use time series of catch data.
- Category 5 - Only commercial landings data are available.
- Category 6 - Only bycatch data are available.

Under this definition, stocks that fall under categories 3 to 6 are considered to be data-limited. While Portuguese octopus could in theory fulfill the data requirements for category 4, currently no advice is given for this stock. Nevertheless, octopus clearly fills the criteria to be treated as a data-limited stock. In *ICES* workshop, on the “Development of

Quantitative Assessment Methodologies based on Life-history Traits, Exploitation Characteristics and other Relevant Parameters for Data-limited Stocks" (*WKLIFE V*) [47], discussed three approaches for assessment of data-limited stocks: length-based methods, catch-only methods and catch-per-unit-effort (*CPUE*) methods [6]. *CPUE* methods encompass surplus production models, which are the only data-limited method that enable a full stock assessment, allowing for the evaluation of exploitation and stock status based on maximum sustainable yield reference points and catch predictions based on alternative scenarios [6]. Due to their low data requirements, surplus production models (*SPM*) are an attractive option for approaching octopus stock assessment, despite some reservations [40].

2.5.1 Surplus Production Models (SPM)

Surplus production models (*SPM*) attempt to model stock dynamics by combining the general effects of growth, recruitment and mortality into a new variable, which is surplus production. The stock is modelled as a one large unit of undifferentiated biomass without taking into account variables age structure, size structure, sex ratios. Consequently, the data requirements are significantly lower than with other methods, with only catch data and an abundance index being needed [6]. The abundance index may be the fishery *CPUE* [6] though it can be argued that a fishery-independent abundance index such as a survey *CPUE* is preferable [40, 48].

A key assumption in *SPM* is the existence of an intrinsic link between changes in catch rates and changes in abundance, such as:

$$\frac{C}{E} = qB \tag{2.1}$$

where C are catches, E is effort spent, B is biomass and q is a constant, often referred to as catchability coefficient.

Most implementations of *SPM* assume that q is constant throughout the time series, i.e. changes in catch rates are linked to changes in biomass [48]. Factors such as changes in fishing gear and spacial displacements of the stock biomass can also affect catchability. [6, 48]. A common practice is then to standardize the abundance index. While are several approaches to achieve this goal [48], a common approach is often through the use of a Generalized Linear Model (*GLM*) with the observed effort as response variable and variables such as month, year, region, engine power and vessel dimensions as predictors. The predictions of this model are treated as the deterministic part of the catch-effort dynamic, where the variance lost in the process is treated as the noise introduced by changes in catchability of the stock and operationality of the fleet [48].

The general structure of a *SPM* can be described as:

$$B_{t+1} = B_t + f(B_t) - C_t \tag{2.2}$$

with B_t as the stock biomass at the beginning of the year t, C_t as the biomass caught in the year t and $f(B_t)$ as the production of biomass function [6].

Therefore, a link between this model, observed catches C_t and the standardized index of relative biomass I_t can be established by defining a catchability coefficient q as the proportion of the total stock taken by one unit of fishing effort. Thus:

$$qB_t = \frac{C_t}{E_t} = I_t \tag{2.3}$$

The baseline model for the production of biomass function was proposed by Schaefer (1954, in [6]) is:

$$f(B_t) = rB_t \cdot (1 - \frac{B_t}{K}) \tag{2.4}$$

with r being the intrinsic rate of population natural increase and K the carrying capacity of the population, i.e. the maximum size capable of supporting positive growth. Since this model results in a symmetric production curve (Figure 2.6), a more general formulation was proposed by Pella and Tomlison [49] that allows asymmetry in the production curve by introducing a new parameter p:

$$f(B_t) = \frac{r}{p} \cdot B_t \cdot (1 - (\frac{B_t}{K})^p) \tag{2.5}$$

The introduction of asymmetry allows for scenarios where maximum surplus production occurs at different stages of the stock in terms of relation between current biomass B_t and carrying capacity K. This formulation becomes equivalent to Schaefer's formulation when $p = 1$. For all other values of p, direct comparison of the parameter estimates of both models is not possible [6, 50].

Other formulations of the model are possible, such as the one proposed by Fox [52], although less frequently applied [6]. This formulations is equivalent to the formulation of Pella and Tomlison when p approaches 0 [6, 50]:

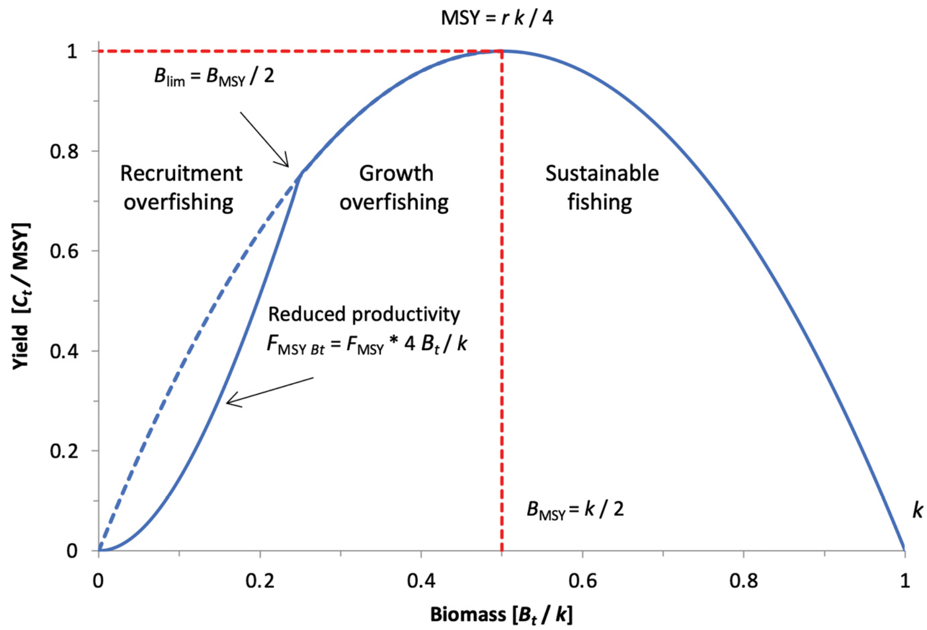


FIGURE 2.6: Production curve of a Surplus Production Model with the Schaefer formulation [51].

$$f(B_t) = Ln(K)rB_t\left(1 - \left(\frac{Ln(B_t)}{Ln(K)}\right)\right) \tag{2.6}$$

These formulations all assume that stock biomass gravitates towards a state of equilibrium. The term rB_t represents unconstrained growth, whereas $\frac{1/p}{(\frac{B_t}{K})^p}$ constrains that growth by tending towards 0 as B_t increases, acting as a density-dependent effect [50].

Based on these models, it is possible to calculate estimates that can serve as biological reference points [50]:

- *Maximum Sustainable Yield* (MSY) is an estimate for maximum biomass removal by fishing or harvest without exceeding the capability of the stock to recover towards maximum surplus production:

$$MSY = \frac{rK}{(p+1)^{\frac{p+1}{p}}} \tag{2.7}$$

- *Biomass Maximum Sustainable Yield* (B_{MSY}) is the estimated biomass levels that should produce the maximum surplus, when the stock is the state of providing MSY.

- *Maximum Sustainable Effort* (E_{MSY}) is the fishing effort that should be maintained in order to push the stock towards MSY equilibrium:

$$E_{MSY} = \frac{r}{q(1+p)} \tag{2.8}$$

- *Maximum Sustainable Fishing Rate* (F_{MSY}) is the proportion of stock that can be removed each year while still allowing the stock to trend towards MSY equilibrium:

$$F_{MSY} = qE_{MSY} = q \cdot \frac{r}{q(1+p)} = \frac{r}{1+p)} \tag{2.9}$$

2.5.1.1 Catch MSY + Bayesian Schaefer Model (CMSY++)

CMSY++ refers to an advanced state-space Bayesian method for stock assessment that was proposed by Froese *et al.* [53]. The approach is based on a modified Schaefer *SPM* and allows for the estimation of reference points such as MSY, F_{MSY}, B_{MSY} and stock status indicators like relative stock size (B/B_{MSY} and exploitation (F/F_{MSY}).

The modified *SPM* is [51]

$$B_{t+1} = B_t + \frac{4B_t}{K} r \left(1 - \frac{B_t}{K}\right) B_t - C_t | \frac{B_t}{K} < 0.25 \tag{2.10}$$

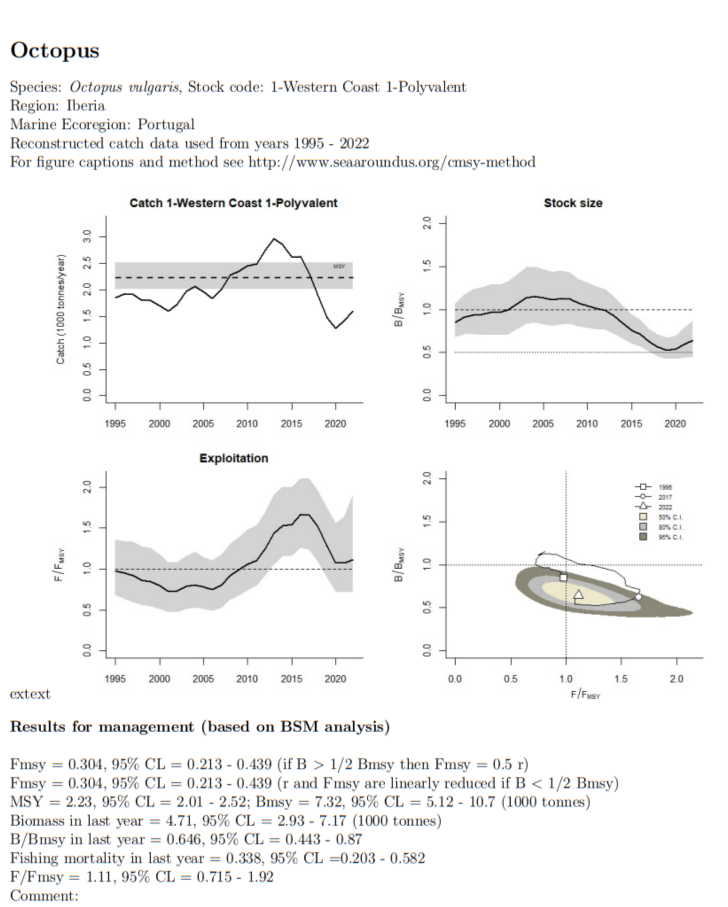
The addition of the $\frac{4B_t}{K}$ term penalizes the recruitment rate at low biomass levels, which is the expected behaviour in such scenarios [51]. This penalization is carried over to the F_{MSY} estimation ($r/2$ in Shaefer's formulation). This allows and accounts for the variation of r over the time series without requiring additional parametrization.

The framework is divided into a part that deals only with catch data (Catch MSY - *CMSY*) and a part that incorporates both catch and abundance data referred to as Bayesian Schaefer Model (*BSM*). In the *CMSY* method, viable $r - k$ pairs are tested by plotting thousands of biomass trajectories in a Monte Carlo ensemble. Combinations of $r - k$ that are plausible (i.e., do not lead to unreasonable scenarios such as inevitable stock crash or sustained biomass close to K under overfishing) are then used for MSY estimation by using the geometric mean of the viable r and K estimates [54].

The *BSM* method is a Bayesian state-space *SPM* implementation. The model requires initial estimates for the ranges of r, K, B/K and a large focus is placed on optimizing the process of these estimates. *CMSY++* is distributed with a pre-trained neural network to determine a estimate for initial B/K. This network was trained by the authors on hundreds of test stocks [51, 53]. Changes in methodology and initial distribution assumptions for the distribution of r and K are presented as the more significant improvements from previous versions of this framework.

CMSY++ has been used for stock assessment in several studies and published reports. A large-scale study aiming to assess the status of global marine fisheries used this method to evaluate more than 2500 stocks worldwide, under the "Sea Around Us" research initiative [55]. At the date of publishing, the authors had identified 58 studies who used *CMSY++* for stock assessment. Since the publication of that paper, more works have been published that rely on *CMSY++*, such as the assessment of blue shark (*Prionace glauca*) [56], Yellowfin tuna (*Thunnus albacares*) in the Indian Ocean [57] or the status of the *Raja clavata* in the Balearic Islands [58]. There are, however, comparatively fewer applications for cephalopod stocks. Some examples include the assessment of squids in the Northeastern South China Sea [59] and cephalopods stocks in the straits of Sicily [60], which found octopus stocks to be in either critical condition or recovering. *CMSY++* was used in an work targetting both pollack (*Pollachius pollachius*) and common cuttlefish (*Sepia officinalis*), and *WGCEPH* has experimented the latter species [61] by using it for european cephalopods stock assessment [22].

CMSY++ is distributed as a stand-alone script, with supplementary material such as the weights for the neural network and extensive documentation bundled together available at `https://oceanrep.geomar.de/id/eprint/52147/`. The most notable requirement is the dependence on *Just Another Gibbs Sampler* (*JAGS*, available at `https://sourceforge.net/projects/mcmc-jags/files/`), which must installed and available at the operative system level, instead of being installed as a package. One of its most notable features is the automated compilation of *LaTeX* reports with plots and estimates organized in a succinct fashion (Figure 2.7).



Octopus

Species: *Octopus vulgaris*, Stock code: 1-Western Coast 1-Polyvalent
Region: Iberia
Marine Ecoregion: Portugal
Reconstructed catch data used from years 1995 - 2022
For figure captions and method see http://www.seaaroundus.org/cmsy-method

extext

Results for management (based on BSM analysis)

Fmsy = 0.304, 95% CL = 0.213 - 0.439 (if B > 1/2 Bmsy then Fmsy = 0.5 r)
Fmsy = 0.304, 95% CL = 0.213 - 0.439 (r and Fmsy are linearly reduced if B < 1/2 Bmsy)
MSY = 2.23, 95% CL = 2.01 - 2.52; Bmsy = 7.32, 95% CL = 5.12 - 10.7 (1000 tonnes)
Biomass in last year = 4.71, 95% CL = 2.93 - 7.17 (1000 tonnes)
B/Bmsy in last year = 0.646, 95% CL = 0.443 - 0.87
Fishing mortality in last year = 0.338, 95% CL =0.203 - 0.582
F/Fmsy = 1.11, 95% CL = 0.715 - 1.92
Comment:

FIGURE 2.7: Excerpt of an automated report created with *CMSY++*.

2.5.1.2 Just Another Bayesian Biomass Assessment (JABBA)

JABBA stands for *Just Another Bayesian Biomass Assessment*, a reference to the aforementioned *JAGS* and is an alternative *SPM* method created by Winker *et al.* [62]. The package implements a generalised Bayesian statespace *SPM*, where the posterior distributions of all parameters are estimated through a Markov Chains Monte Carlo (*MCMC*) simulation. The *SPM* formulation implemented is a modified version of Pella-Tomlison's:

$$B_{t+1} = B_t + \frac{r}{m-1} \cdot \frac{Bt}{P_{lim} \cdot K}\left(1 - \frac{B_t}{K}\right)^{m-1} - C_t \; if \; \frac{Bt}{K} < P_{lim} \tag{2.11}$$

With:

$$P_t = \frac{B_t}{k} \quad \text{and} \quad P_{lim} = \quad \text{user defined} \tag{2.12}$$

The variable P_t is the proportion between biomass at time t, B_t and the carrying capacity K. To improve the efficiency of the algorithm in the state space implementation, P_t is the variable that is explicitly modelled. Thus, P_{lim} represents a threshold, manually set by the user, under which biomass estimates are penalized. As in *CMSY++*, the authors addressed the concern that Schaefer's formulation would behave unrealistically at low biomass levels, since the original model does not account for a diminished recruitment that results from a drastic decrease in spawning biomass. The added modifier $\frac{Bt}{P_{lim} \cdot K}$ is applied whenever B_t/K falls below P_{lim}. Should P_{lim} be set to a value higher than the estimate for B_{MSY}/K, *JABBA* is programmed to replace the setting with B_{MSY}/K. Maximum surplus production should be attained at the inflection point, so applying the penalization for P_t values above that point would be an over-correction [62]

The notation used by the authors is a variation where the asymmetry parameter p is replaced by the term $m-1$. While this change is inconsequential from a mathematical point of view, it does have implications for describing and parameterizing the model. This formulation converges to Schaefer's model (Equation (2.4) when $m = 2$, as opposed to $p = 1$ and converges to Fox's model (Equation 2.5) when m approaches 1, instead of 0.

The stochastic form of the process equation ([62]) is, as previously mentioned, defined in order of P_t :

$$P_y = \begin{cases} \varphi e^{\eta_y} \quad \text{for} \quad y = 1 \\ \left(P_{y-1} + \frac{r}{m-1} P_{y-1} (1 - P_{y-1}^{m-1}) - \frac{\sum_f C_{f,y-1}}{K} \right) \cdot e^{\eta_y} \quad \text{for} \quad P_{y-1} \geq P_{lim} \quad \& \quad y = 2, \dots, n \\ \left(P_{y-1} + \frac{r}{m-1} P_{y-1} (1 - P_{y-1}^{m-1}) (\frac{P_{y-1}}{P_{lim}}) - \frac{\sum_f C_{f,y-1}}{K} \right) \cdot e^{\eta_y} \quad \text{for} \quad P_{y-1} < P_{lim} \quad \& \quad y = 2, \dots, n \end{cases} \tag{2.13}$$

where $C_{f,y}$ is the catch from fishery f in the year y. The biomass for year y is given by $B_y = P_y K$. The observation equation is given by:

$$I_{i,y} = q_i B_y e^{\epsilon_{y,i}} \quad y = 1, 2, \cdots n \tag{2.14}$$

This model incorporates process error through the inclusion of the term η_y, with $\eta_y \sim N(0, \sigma_\eta^2)$. *JABBA* allows the user to either estimate the process variance σ_η^2 or set it to be fixed. It also incorporates observation error in the term $\epsilon_{y,i} \sim N(0, \sigma_{y,i}^2)$. This formulation accommodates the incorporation of data from multiple fleets (f, i) in the estimation.

JABBA [63] is an*R* package available at: https://github.com/jabbamodel/JABBA. It can be installed as an R package through *devtools*, though cloning the repository and editing the prime script is the workflow described in the documentation. Like *CMSY++*, *JABBA* relies on an operating-system-level installation of *JAGS*. While missing catch data is not allowed, missing abundance index data is possible. Data must be aggregated to an yearly time step.

Currently, five *ICCAT* stocks are assessed through *JABBA* [6]. Some published works featuring the use of this method include the assessment of the Atlantic stock of blue marlin (*Makaira nigiricans*) [64], the Atlantic stock of yellowfin tuna (*Thunnus albacares*) [65], the North and South Atlantic stocks of shortfin mako (*Isurus oxyrinchus*) [66], the South Atlantic stock of albacore tuna *Thunnus alalunga*) [67], the Atlantic porbeagle *Lamna nasus*) [68], among many others.

2.5.1.3 A Stochastic Surplus Model in Continuous Time (SPiCT)

SPiCT is a *SPM* method proposed by Pederson & Berg [69], that aims to address some perceived shortcomings of previous implementations. It is defined in continuous time, modelling both biomass and fishing dynamics as states observed indirectly through biomass indices and commercial catches [6]. It allows for sub-yearly data aggregation and incorporation of seasonal patterns, and it accounts for observation errors on both catch and abundance index data. It is based on the continuous formulation of Pella-Tomlinson's model [69]:

$$\frac{dB_t}{dt} = \frac{r}{p} B_t \left(1 - \left(\frac{B_t}{K}\right)^p\right) - F_t B_t \tag{2.15}$$

To facilitate estimation, the model is reparameterized as:

$$\frac{dB_t}{dt} = \gamma m \frac{B_t}{K} - \gamma m \left(\frac{B_t}{K}\right)^{p+1} - F_t B_t \tag{2.16}$$

with:

$$\gamma = \frac{(p+1)^{\frac{p+1}{p}}}{p} \quad \text{and} \quad m = \frac{rK}{(p+1)^{\frac{p+1}{p}}} \tag{2.17}$$

A stochastic term W_t with Brownian motion is then added into the model to account for environmental and ecological factors that cannot be explicitly incorporated into the model due to lack of available data:

$$dB_t = \left(\gamma m \frac{B_t}{K} - \gamma m \left(\frac{B_t}{K} \right)^{p+1} - F_t B_t \right) dt + \sigma_B B_t dW_t \tag{2.18}$$

In order to prevent instability in the model fitting brought about by the multiplicative error term, the model is logarithmized:

$$dZ_t = \left(\frac{\gamma m}{K} - \frac{\gamma m}{K} \left(\frac{e^{Z_t}}{K} \right)^{p} - F_t - \frac{1}{2}\sigma_B^2 \right) dt + \sigma_B dW_t \tag{2.19}$$

with

$$Z_t = log(B_t) \tag{2.20}$$

In *SPiCT*, instantaneous fishing mortality rate F_t is explicitly modeled as an unobserved process, instead of being estimated in discrete time as C_t/B_t [6, 69]. *SPiCT* models F_t as the product of seasonal (S_t) and random (G_t) components:

$$\begin{aligned} F_t &= S_t G_t \\ dlogG_t &= \sigma_F dV_t \end{aligned} \tag{2.21}$$

with dV_t being Brownian motion and σ_F the standard deviation of F. If only annual data is available, then S_t is fixed at 1. For sub-annual data, seasonal variations in the fishing rate can be modelled through either the use of a cyclic spline or a system of stochastic differential equations [69]. While the second option is more flexible and capable of adapting to changes in amplitude and phase of seasonal fishing patterns, it is also more complex and more prone to convergence failure [6].

At this stage, observed catch can be modeled as:

$$log(C_t) = log\left(\int_t^{t+\Delta} F_s B_s ds \right) + \epsilon_t \tag{2.22}$$

where C_t is the cummulative catch over Δ_t and $\epsilon_t \sim N(0, \beta\sigma_C^2)$ are catch observation errors.

The observation indexes are modelled by:

$$log(I_{t,i} = log(q_i B_t) + e_{i,j},\ e_t \sim N(0, \sigma_{t,i}^2) \tag{2.23}$$

SPiCT supports the inclusion of more than one series pertaining to the fishery. In this context, for abundance index i, q_i is the catchabilty coefficient for I_i and $\sigma I, i$ is the standard deviation of I_i.

SPiCT is available as a *R* package [69], available at: `https://github.com/DTUAqua/spict`. It is extensively documented, with several vignettes and handbooks. Plotting methods rely on *R* base plots and there are several built-in diagnostic plotting tools.

SPiCT is currently the most used *SPM* at both the General Fisheries Commission for the Mediterranean (*GFCM*) and *ICES*, and its application in formal assessments is expected to continue increasing in coming years, since several stocks have had preliminary analyses conducted such as Hake in Geographical Sub-Areas (GSA) 20, 22, 23 or Sardine GSA 3 stocks assessed by the *GFCM* [6, 70]. Preliminary work was conducted in some cephalopod stocks in the Northeastern Atlantic, including octopus, with mixed results [71]. *SPiCT* was also applied to horned octopus *Eledone cirrhosa* [60, 72]. *WGCEPH* currently considers *SPiCT* applicability to cephalopod stocks moderate at best and is actively researching alternative approaches [22].

2.5.2 Generalized Depletion Models (*GDM*)

One of the main assumptions of surplus production models (*SPM*) relies on stock stability around the maximum sustainable yield (*MSY*) equilibrium [6] as a consequence of demographic inertia, with older cohorts supporting recruitment. With cephalopods being semelparous, the reduced overlap between generations is often the source of objections of the adequacy of *SPM* for modelling cephalopod stocks. The very concept of *MSY* as an adequate target yield for fisheries management has been questioned [32].

An alternative modelling approach, often used for squid stock assessment [73], is based on generalized depletion models [32]. This approach has been incorporated in the management of octopus fisheries in Asturias (Spain) and is currently being assessed on the Algarve octopus fishery.

A depletion model assumes for the duration of assessment a homogeneous cohort forming a closed population, linear relationship between catch rate and abundance, constant catchability, constant natural mortality, and actual decline of the catch rate [73]. Depletion models work with short time steps such as days or weeks, which is advantage for species with fast dynamics such as cephalopods [73]. While *GDM*s do not directly provide stock status indicators, they focus on modelling the catch dynamics as a response to fishing effort and stock abundance, thus allowing the estimation of two very important parameters: stock abundance and natural mortality [74].

The most simple formulation of a depletion model is based on the classic DeLury formulation of a linear relationship between $CPUE$ and cumulative catch [75–77]:

$$
\begin{aligned}
N_t &= N_0 - K_T \\
CPUE_t &= \frac{C_t}{E_t} = qN_t \longleftrightarrow \\
CPUE_t &= qN_0 - qK_t
\end{aligned}
\tag{2.24}
$$

Where N_0 and N_t are number of individuals at the beginning of the series at time t respectively and K_t, unlike in the context of production models, represents cumulative catch at time t. A variation of this model that accounts for natural mortality rate M and varying fishing effort was proposed by Rosenberg [75]:

$$
N_{t+1} = \left(N_t e^{-\frac{M}{2}} - C_t\right) e^{-\frac{M}{2}} \tag{2.25}
$$

under this model, the catch of a fleet j over a time period t with effort E_t is given by the catch equation:

$$
c_{tj} = q_j E_{jt} N_t e^{-\frac{M}{2}} \tag{2.26}
$$

Based on the population depletion model (Equation 2.25) and observation model (Equation 2.26), parameters can then be estimated through maximum likelihood [76]. For a fishery $CPUE$ time series, a depletion model can predict the point at which the population would be reduced to a pre-determined stock size threshold, and, after accounting for growth and natural mortality, the initial population size can be back-calculated [73].

In their basic formulations, depletion models assume a closed population, a linear dependency between $CPUE$ and abundance and a constant natural mortality rate, which often can not be met [73, 78]. Practical implementations of generalized depletion models address some of these assumptions by incorporating recruitment pulses and variation on the effort-response to abundance [32, 73, 78].

Generalized depletion models have been extensively used for stock assessment in squid fisheries. Arkhipkin [73] recounted 18 different squid stocks which had been assessed in this fashion, spanning from 1983 to 2016 and places such as Japan, Falkland, California or the English Channel. It has also been applied to other cephalopods such as cuttlefish and, more recently, octopus [32].

2.5.2.1 Fishery Stock Assessment by Catch Dynamics Models (CatDyn)

CatDyn [74] is an hierarchical approach for stock assessment where catch dynamics are modelled in relation to fishing effort E_t and abundance in numbers N_t through a modified *GDM* that assumes the fishery to be open and therefore incorporates pulses in abundance from spawning batches and migrations as discrete perturbations in the model:

$$\begin{aligned} C_t = kE_t^{\alpha} N_t^{\beta} &= mkE_t^{\alpha} f_t(M, N_0, C_{i<t}, R, S) \\ \text{with} \quad m &= e^{-\frac{M}{2}} \end{aligned} \tag{2.27}$$

where parameters α and β modulate the strength of non-linear effects on effort and abundance, respectively [32, 74]. α spans the continuum from effort saturation ($\alpha < 1$) through proportionality ($\alpha \approx 1$) to synergy ($\alpha > 1$) and β ranges from abundance hyperstability ($\beta < 1$) through proportionality ($\beta \approx 1$) to hyperdepletion ($\beta > 1$) [32]. f_t incorporates the perturbations caused by spawning and migration pulses as:

$$C_t = kE_t^{\alpha} m \left(N_0 e^{-Mt} - m \left[\sum_{i=i}^{i=t-1} C_{i,i} e^{-M(t-i-1)} \right] + \sum_{j=1}^{j=u} I_j R_j e^{-M(t-\tau_j)} - \sum_{l=1}^{l=v} J_l S_l e^{-M(t-v_l)} \right)^{\beta} \tag{2.28}$$

In this complete formulation, C represents expected catch in numbers, M natural mortality rate (with m being an adjustment to make the catches happen instantaneously at the middle of the time step), R the recruitment magnitude and S the female spawners magnitude. I and J are indicator variables that take a value of 0 before the event and 1 after. τ and v are the indexes of the perturbations [32].

The observed catch is modelled as a time series with the mean given by Equation 2.28 and a distribution to be determined, with normal, lognormal, negative binomial and gamma distributions being some possible starting options [32, 79]. Biomass at time step t can then be estimated by [79]:

$$\hat{N}_t = \hat{N}_0 e^{-Mt} + \sum_l I_{t,l} \hat{R}_{1,l} e^{-M(t-\tau_l+1)}, \hat{B}_t = \hat{N}_t \hat{w}_t \tag{2.29}$$

CatDyn [80] is a multi-annual framework where the catch dynamics of each fishing season are modelled individually. All parameters from this model must be estimated and can not be set at fixed values [79]. The data concerning landings and fishing effort from each fishing season is aggregated to a weekly or monthly time step. Supplementary data regarding mean individual weight for each time step must also be obtained, in order to convert catch weight into numbers. Each season is examined for the occurrence of catch spikes, which are defined as [32]:

$$Spike_t = 10\left(\frac{\chi_t}{max(\chi_t)} - \frac{E_t}{max(E_t)}\right) \tag{2.30}$$

High values in the catch spike statistic may denote the occurrence of a recruitment pulse and low values may be associated with emigration. The time indexes t of these spikes are then plugged into the I and J indicator variables to be plugged into Equation 2.28. Several combinations of catch spike lists, catch distribution and other hyperparameters (such as optimizer algorithm) can be tested. Implausible estimates can be excluded, such as those which result in estimates for natural mortality M larger than 0.1 or smaller than 0.01 [32]. The best fit is then selected manually by examining the correlation matrix of parameter estimates and selecting the model with the least correlated estimates (≈ 0).

Once all seasons have been fit with a catch dynamic model, the entire series can then be reconstructed using estimates from the earlier years to propagate forward into the initial conditions of the succeeding fishing season. Estimates for the abundance, natural mortality and fishing mortality (obtained through the inversion of Baranov's catch equation [32, 74]) can then be used in the second stage of the hierarchical framework. This stage consists of the application of another stock assessment model that is applied to the modelled series, rather than the raw data and its inherent uncertanties on stock dynamics.

Some reported applications of *CatDyn* include abundance estimates of Patagonian longfin squid (*Loligo gahi*) in the Falklands [78] and Narrow-barred Spanish mackerel (*Scomberomorus commerson*) in the Arabian Gulf [81], where *CatDyn* was used to directly assess the stock through estimates of abundance, depletion and fishing mortality rate. In its application to the Chilean sea urchin (Loxechinus albus) [74], estimates from the *GDM* where used to fit a *SPM* to the fishery data. A *SPM* was also used for the second stage of the assessment with the fishery of Common two-banded seabream (*Diplodus vulgaris*) in Southern Portugal [79]. For *Octopus vulgaris* in Asturias, however, the method chosen for the second stage of the assessment was a selection of formulations for Stock-Recruitment models [32].

CatDyn is distributed as an *R* package that is directly avaliable on *CRAN* on: https://cran.r-project.org/web/packages/CatDyn/index.html. All of its dependencies are handled through the package installation routine, requiring no previous setup from the user. It features diagnostic plots and tools to initialize data into its own custom class and fit the *GDM* to each fishing season, as well as a function to use all model fit objects to back-calculate the abundance estimates for the entire series. Methods for the second stage of the framework are not provided and are left to the discretion of the user.

2.5.3 Summary of methods considered in this work

A quick comparison of the stock assessment methods reviewed in this work is presented in Table 2.1. It should be noted that *CatDyn* is not directly comparable to the *SPM* methods, since its output is estimates of real catch per time step, whereas *SPM* directly estimate biological reference points such as r, k, *MSY* among others. *CatDyn* is therefore only included in the table for the sake of completeness.

TABLE 2.1: Overview of the stock assessment methods considered in this work.

Property	*CMSY++*	*JABBA*	*SPiCT*	*CatDyn*
Time	Discrete	Discrete	Continuous	Discrete
Time step	Yearly	Yearly	Custom	Sub-yearly
Observation Error	Yes	Yes	Yes	
Index Error	No	No	Yes	
Process Error	Yes	Yes	Yes	
Format	R script	R package	R package	R package

2.5.4 Other methods not considered in this work

There are several alternative methods for implementing *SPM* that were not examined in this work.

ASPIC (A Stock-Production Model Incorporating Covariates) implements a continuous non-equilibrium *SPM* [82]. It is available on https://www.mhprager.com/aspic.html as a standalone installer. While it is an older framework, it still currently used to formally assess 2 stocks in *NAFO* and 1 in *ICCAT* [6].

Other production models software are still widely used in *ICCAT*, for example a generalized *Bayesian Surplus Production* stock assessment software (*BSP2*), which is presented as an update to *BSP* software [83].

While *CatDyn* is arguably the most current implementation of *GDM* that is under active research and development, some other tools that relied on these type of models include *MSQUID* [84] and *CEDA* [85]. Both tools were used to monitor fisheries in-season [73].

Having established the background and motivation for this work, the methodology to tackle the challenge of octopus stock assessment that was used in this work will be described in the following section.

Chapter 3

Methodology

In this chapter, the steps taken at each stage of this work are described. Data sources are presented and data transformations are explained. For each method, steps taken to input the data and the parametrization used are presented and the rationale behind key decisions made at this stage is discussed.

All *R* code and related outputs developed throughout this work are available on https://github.com/AJSRocha/msc_ds_thesis, with the exception of the source code for the *Shiny* prototype that will be discussed below, which is available separatly on https://github.com/AJSRocha/msc_ds_app_v2. The *Shiny* app itself is deployed at https://albertorocha.shinyapps.io/msc_ds_app_v2/.

3.1 Data Collection

3.1.1 Commercial landings data

Daily data for octopus landings in the portuguese auction markets is made available by the *Direcção-Geral de Recursos Naturais, Segurança e Serviços Marítimos* (DGRM) for the *Instituto Português do Mar e da Atmosfera* (IPMA). The data available for this work covered the years between 1995 and 2022, for all fishing ports in Continental Portugal. Available data for each commercial transaction regarding octopus included quantity landed in kg, commercial denomination, size category, date and port of sale and fishing gear information.

Commercial denominations are a source of uncertainty when analysing fisheries data. Erroneous usage of the 3-letter FAO code during the sale at the fish auction markets is rampant. This phenomenon is often rooted in either a mismatch of traditional used names for the species and their scientific *taxa* or mistakes in the informatic system (sometimes compounded by hamfisted data aggregation pipelines). In the case of *Octopus vulgaris*, the correct 3-letter FAO code 'OCC' is commonly used, though usage of the more generic 'OCT' has been found, which stands for the family *Octopoda*. This denomination used to also encompass landings of *Eledone cirrhosa* and *Eledone moschata* [86, 87]. The extent of *Eledone* spp. landings that were reported while aggregated with *Octopus vulgaris* landings is unknown [88]. The use of this denomination was residual (with 14 uses in daily sales data) by 2013 and no records were found after 2016, marking a transition for more correct codes for *Eledone* spp. No other instances of suspect species identification were found during the data analysis.

Size category in fish auction markets is assigned based on a categorical scale determined by the Regulation N.º 2496/96 (EU) [89]. The scale assigns a number reflecting the overall dimensions of the specimens in each individual fish box during the sale, with '1' being given to larger specimens and higher numbers, typically up to '6', being given to smaller specimens. For octopuses, it is uncommon to assign a size category smaller than '3'. Portuguese Fishing Markets are managed by a public company, DOCAPESCA, S.A. [90], which reports sales data to *DGRM* on a port by port basis. Patterns on size category attribution are very dependent on the port, with many ports not reporting size categories at all, instead reporting a '0' size. This fact makes size-based sampling and their respective extrapolations to the overall landings difficult and prevents the use of size category as a predictor in the analysis of this particular stock.

Fishing gear information is provided for each fishing trip, at a group level (distinction between bottom trawlers, purse-seiners and polyvalent fleet), gear type level (pots, traps, gill nets, etc...) and specific gear levels (type of pots, mesh sizes...). Such information could prove very useful for proper data segmentation and improved fishing effort estimations. Problems arise, however, when analysing data regarding the smaller-scale, artisanal vessels. Such vessels typically operate with several licenses and will use 2 or 3 different gear types on a single trip [91, 92]. This makes correlating catch with gear used (and, consequently, effort) problematic. In the dataset used for this work, trips were assigned to gear type and specific gear levels algorithmically by the DGRM, whose definition of gear segment may or may not align with the practical considerations for this work. For this reason, official landings were segmented in two large groups: 'OTB', corresponding to the bottom trawlers and 'MIS', corresponding to the mixture of smaller, artisanal fishing gears used by small scale fisheries. Landings from the Purse Seine segment ('PS') were removed from the dataset due to the residual occurrence of octopus in this fishery. Results pertaining to the polyvalent fishery of octopus are examined in detail in this document. The bottom trawl fishery, whose landings account for less than 10% of the total octopus landings, was evaluated separately and the results are included in Appendix A, for reference.

The 'MIS' group aggregates several types of fishing gear, many of which do not target octopus. In an attempt to prevent their inclusion in the effort estimation, for each year and each vessel the average percentage of octopus was calculated. Based on that, a cutoff point was estimated, with vessels who only exceeded that cutoff being considered as actively targeting octopus.

3.1.2 Effort estimation

As discussed previously in Chapter 2, robust effort estimations are necessary for most of the stock assessment methods employed in this work, which use catch-per-unit-of-effort (CPUE) or landings-per-unit-of-effort (LPUE) as abundance indexes for the fishery.

For the bottom trawl fishery, some common choices for measuring fishing effort are time spent trawling/day or kW of engine power deployed/day [93]. This fishing gear is an active gear and therefore it is a safe assumption that larger catches will be correlated with longer deployments.

However, for the polyvalent fishery, which consists mostly of traps and pots, this relationship is more tenuous. Unlike fish, octopus are not effectively trapped in the pots, being able to use them freely as shelter and leaving at will. This fact, combined with the scarcity of information on how many traps and pots each vessel has deployed, for how long, and how many are hauled on any given trip, makes effort estimation for the polyvalent fishery problematic.

An approach that has been used in previous works [71] consists in counting fishing days, *ie* the number of fishing days that resulted on a reported landing from the fleet, aggregated to a given time step. This was the approach considered for this work both the bottom trawl and the polyvalent fleets. Other alternatives available would have been basing the index on trips that are known to have lasted a single days, as in [94], but it was impossible to implement this approach in a timely manner.

Trawling duration would have provided a more granular and accurate effort index for the bottom trawling fleet, but in this particular case there are several considerations against using it. It would be harder to compare the results for both fleets if the effort estimation approach were significantly different. Octopus is mostly a bycatch in the bottom trawling fishery due to the typical depths that the fleet operates in, so higher effort may not result in higher octopus yields if the effort is directed in such a way that actually reduces catchability for octopus by focusing on higher depths [15]. Lastly, calculating trawl duration for each relevant trip would have required logbook data which would have required an additional release authorization for its use in this work.

Therefore, effort was calculated in fishing trips per time step, for both fleets. Nominal landings per unit of effort (LPUE) for were calculated as:

$$LPUE_i = \frac{\sum_{j=1} catch_j}{total_j} \tag{3.1}$$

where i is the timestep and j is the fishing trip event. $total_j$ is the number of trips in the timestep i, representing the effort measure for that period.

3.1.3 Effort standardization

Because the abundance index chosen is fishery-dependent, it would be desirable to standardize on the *CPUE* in order to remove the effects of catch-rate changes which are not a result of shift in biomass abundance, but instead are caused by other factors such as changes in fishing gears, fishing patterns, overall fleet capabilities, spacial migrations, among others.

However, for this work, the use of a discrete measure for effort in the form of fishing trips as an effort estimator is a non-conventional choice that raises additional concerns for selecting an optimal approach for standardization.

Two approaches were attempted for standardizing the *LPUE* series in this work: Modulating the *LPUE* series through estimation of the Efficiency Power of each fishing gear, as per [95] and modeling *LPUE* through a Generalized Linear Model with a Tweedie distribution. This link function was chosen due to the very high occurrence of extreme values in the distribution (trips that did not target octopus, and therefore landed 0, or trips that solely targeted this species and landed nothing else). The Tweedie distribution is frequently used in stock assessments with such distributions [96].

3.1.4 Initial processing and exploration

Daily sales date from the fishing auction markets was imported and processed in R [3], using *dplyr* [97] and *ggplot2* [98].

Portuguese landings from the northwestern coast (ICES subarea 27.9.a.c.n) and the southwestern coast (ICES subarea 27.9.a.c.s) were grouped together as 'West Coast' landings. Landings from ICES subarea 27.9.a.s.a were assigned to a second group, 'South Coast'.

The remaining landings, concerning the portuguese autonomous regions of Açores and Madeira were removed from the dataset. At this stage, landings from the Purse Seine fleet were also removed.

The original dataset is structured in such a way that for each fishing trip there are several observations, corresponding to separate sale acts. The dataset was aggregated to a single observation per fishing trip, with 2 new variables being calculated: weight of octopus landed (kg), resulting from the sum of landings reported with the FAO codes 'OCC' and 'OCT', and weight of the total landing of each trip (kg). Based on the date of sale, variables encoding the year, month and week were created. These variables were used to aggregate the dataset to different time steps, depending on the requirements of the method in question.

The resulting dataset was functionally divided in 4 different groups, split across 2 different fleets (Bottom Trawl vs. Polyvalent) and 2 Regions (West Coast vs. South Coast). Based on this dataset, 2 new dataframes were created, aggregating the data by year and by week. At this stage, catch per timestep, effort by timestep and nominal LPUE were calculated.

The final landings series were then tested for stationarity and whether an autocorrelation structure was present. For this purpose, data was aggregated to weekly and yearly time steps. Both scenarios were analysed separately. At this stage, data had to be converted to the *ts* class from the *stats* package [3]. Because this requirement was exclusive to this approach, execution time for the conversion was recorded and included in the performance assessment. Each series was tested for stationarity with the augmented Dickey-Fuller test as implemented in the *tseries* package [99]. The functions *ndiffs()* and *nsdiffs()* from the *forecast* package [100] were used to detect whether non-seasonal and seasonal differentiation were recommendable for each time series.

3.2 Assessment methods

The comparison of the different methods examined in this work focused on their suitability for two different challenges. Whether they can be used, at least on a basic capacity, to fit stock assessment models to the Portuguese octopus landings data, and whether they can be easily adapted to be integrated into more complex methods, such as serialized or distributed computation of model fits or wrapped in interfaces such dashboards or remote applications in order to be made more accessible.

The first question is addressed by applying each method to the same dataset and compare the stock assessments that are possible based on the results. The second question is addressed by examining, for each method, implementation types, dependencies, default choices, input specifications, output limitations and execution times.

While most of these criteria are hard to quantify, as a whole they can be a good indicator of possible limitations that are met when trying to use these methods outside the exact use case they were conceived for. In order to test the adaptability of each method, a protopype App was developed with *Shiny* [101] and *flexdashboard* [102] where the analysis performed in this work was adapted in order to be executable in an interactive way.

The criteria that is easier to quantify is execution time. All trials for each method and dataset were divided into three stages, which were timed separately. First stage was the data ingestion stage, where the landings dataset was made compatible into the method's input specifications. Second stage was the model fitting stage, which included the estimation of parameters of the model as well as the construction of any auxiliary objects required by the method, typically a list of priors and hyperparameters. The third stage was the output rendering stage, where the printing of plots and tables and their recording to disk was included.

For all methods, the tasks were structured similarly, with the same datasets as inputs and a similar amount of plots and recorded tables.

3.2.1 CMSY++

CMSY++ is the only method explored in this work that is not distributed in a package. For this method, data must be aggregated by year and the *SPM* model used is the modified Schaefer version (Equation 2.10).

The distributed version consists of a main script over 2400 lines long, where input specifications and customization of outputs are all handled in the first 90 lines. The script is very strict in the format of the input data and it expects the user to create a comma-separated-values file according to specifications which is then imported. This dataframe should include metadata such as 'Continent', Region', 'SubRegion', 'Source' as well as stock-specific priors, such as estimates for initial values of F_{MSY} and B_{MSY} and starting ranges for estimating r and K. Stock resilience was set as 'High', in accordance to the aggregate estimate of $r = 0.81$ presented in [103]. Other prior specifications were left either at their default values or unspecified.

In order to streamline the work, the input section of the script was heavily modified in order to accommodate loading the dataframe directly into the environment in *.RData* format, as was done with the other methods. The second part of the preamble includes several flags related to choices for plot rendering and the *LaTeX* report. Below is presented an example of the modified preamble.

```
id = data.frame(Continent = 'Europe',
                Region = 'Iberia',
                Subregion = 'Portugal',
                Stock = '1-Western Coast 1-Polyvalent',
                Group = 'Cephalopoda',
                Name = 'Octopus',
                ScientificName = 'Octopus vulgaris',
                SpecCode = 'OCC',
                Source = 'DGRM',
                MinOfYear = 1995,
                MaxOfYear = 2022,
                StartYear = 1995,
                EndYear = 2022,
                Flim = '',
                Fpa = '',
                Blim = '',
                Bmsy = '',
                MSYBtrigger = '',
                Fmsy = '',
                last_F = '',
                Resilience = 'High', #'High', 'Medium', 'Low', 'Very Low'
                r.low = NA,
                r.high = NA,
                stb.low = NA,
                stb.hi = NA,
                int.yr = NA,
```

```
                     intb.low = NA,
                     intb.hi = NA,
                     endb.low = NA,
                     endb.hi = NA,
                     e.creep = TRUE,
                     btype = 'CPUE', # 'CPUE', 'None', 'biomass'
                     force.cmsy = FALSE,
                     Comment = '')

CV.C          <- 0.15  #><>MSY: Add Catch CV
CV.cpue       <- 0.2 #><>MSY: Add minimum realistic cpue CV
sigmaR        <- 0.1 # overall process error for CMSY; SD=0.1 is the default
cor.log.rk    <- -0.76 # empirical value of log r-k correlation in 250 stocks
    analyzed with BSM (without r-k correlation), used only in graph
rk.cor.beta   <- c(2.52,3.37) # beta.prior for rk cor+1
nbk           <- 3 # Number of B/k priors to be used by BSM, with options 1 (
    first year), 2 (first & intermediate), 3 (first, intermediate & final bk
    priors)
bt4pr         <- F # if TRUE, available abundance data are used for B/k prior
    settings
auto.start    <- F # if TRUE, start year will be set to first year with
    intermediate catch to avoid ambiguity between low and high bimass if
    catches are very low
ct_MSY.lim    <- 1.21  # ct/MSY.pr ratio above which B/k prior is assumed
    constant
q.biomass.pr <- c(0.9,1.1) # if btype=="biomass" this is the prior range for q
n             <- 5000 # number of points in multivariate cloud in graph panel (b
    )
ni            <- 3 # iterations for r-k-startbiomass combinations, to test
    different variability patterns; no improvement seen above 3
nab           <- 3 # recommended=5; minimum number of years with abundance data
    to run BSM
bw            <- 3 # default bandwidth to be used by ksmooth() for catch data
mgraphs       <- T # set to TRUE to produce additional graphs for management
e.creep.line <- T # set to TRUE to display uncorrected CPUE in biomass graph
kobe.plot     <- T # set to TRUE to produce additional kobe status plot;
    management graph needs to be TRUE for Kobe to work
BSMfits.plot <- T # set to TRUE to plot fit diagnostics for BSM
pp.plot       <- T # set to TRUE to plot Posterior and Prior distributions for
    CMSY and BSM
rk.diags      <- T #><>MSY set to TRUE to plot diagnostic plot for r-k space
```

```
retros       <- T # set to TRUE to enable retrospective analysis (1-3 years less in the time series)
save.plots   <- T # set to TRUE to save graphs to JPEG files
close.plots  <- T # set to TRUE to close on-screen plots after they are saved, to avoid "too many open devices" error in batch-processing
write.output <- T # set to TRUE if table with results in output file is wanted; expects years 2004-2014 to be available
write.pdf    <- T # set to TRUE if PDF output of results is wanted. See more instructions at end of code.
select.yr    <- NA # option to display F, B, F/Fmsy and B/Bmsy for a certain year; default NA
write.rdata  <- F #><>HW write R data file
```

In this setting, both the catch-only estimation (*CMSY++*) and Bayesian Surplus Model (*BSM*) are fitted sequentially. Both estimations are necessary in order to compile the final report, which was included in the requested outputs. For this reason, performance times recorded for the fitting stage of *CMSY++* do not separate both methods and account for them as a whole.

To incorporate *CMSY++* in the *Shiny* app it was necessary to refactor the entire script, in order to separate calculations and plotting methods from their conditional structures and integrate them into reactive environments. While most of the original syntax was kept, the top-down structure of the script that relies on previously created objects required extensive adaptations.

3.2.2 JABBA

JABBA requires data to be aggregated to an yearly time step. Documentation for the *JABBA* package [63] mostly refer to an approach where a prime script with custom inputs and outputs is adapted by the user in order to iterate over several scenarios.

For this work, a simplified version relying on *JABBA* built-in functions was created. The preprocessing is done inside a single function, *build_jabba()*, where data is input as vectors and model priors can be set.

There is an explicit choice for the model formulation, with options being 'Schaefer', 'Pella-Tomlinson' and 'Fox'. This provided a good opportunity to assess the impact of model formulation choice, so the 3 scenarios were tested for both the Polyvalent West and Polyvalent South data sets. For the Pella-Tomlinson model, the inflexion point (B_{MSY}/K

was set arbitrarily at 0.4. P_{lim} was set to 0.25. All other parameters were left as their default values, even when explicitly written, as in the example below:

```
build_jabba(
catch = data.frame('Year' = input$year_sale %>% as.numeric(),
                                        'mis' = input$catch),
                     cpue = data.frame('Year' = input$year_sale %>% as.numeric
   (),
                                        'mis' = input$lpue),
                     se = data.frame('Year' = input$year_sale %>% as.numeric()
   ,
                                        'mis' = log(input$sd/input$lpue)),
                     scenario = 'TestRun',
                     model.type = 'Fox',
                     sigma.est = F,
                     fixed.obsE = 0.01,
                     BmsyK = 0.4,
                     Plim = 0.25)
```

Model fitting was also done in a single step, through the function *fit_jabba()*. Most settings pertain to the fitting process, such as number of iterations and convergence criteria, but at this stage some prior estimates can also be manually set. The prior estimate for r was set to 0.81, as with *CMSY++*. Options were otherwise left in their default values, such as below:

```
fit_jabba(jbinput_w_schaefer,
ni = 30000, #number of iterations
nt = 5, # thinning interval of saved iterations
nb = 5000, #burn-in
nc = 2, #number of mcmc chains initial values
init.values = FALSE, #
init.K = NULL,
init.r = 0.81,
init.q = NULL,
peels = NULL, # NULL, # retro peel option
do.ppc = TRUE, # conducts and saves posterior predictive checks
save.trj = TRUE, # adds posteriors of stock, harvest and bk trajectories
save.all = FALSE, # add complete posteriors to fitted object
save.jabba = FALSE, # saves jabba fit as rdata object
save.csvs = FALSE, # option to write csv outputs
```

```
output.dir = 'scripts/jabba',
quickmcmc = TRUE,
seed = 123,
jagsdir = NULL,
verbose = TRUE)
```

The condensed syntax relying on *JABBA*'s built-in methods that was used on the analysis was transposed into the *Shiny* app without requiring significant adaptations other than those required by the reactive environment. User choices for prior settings and hyperparameters were put in place and the ouput section includes the plots presented in the analysis as well as some choice value boxes.

3.2.3 SPiCT

While *SPiCT* [69] supports sub-annual data, every attempt to fit monthly or weekly aggregated data resulted in failure to converge. Therefore, only annual data was fit and modeled to completion.

Data was vectorized and assembled into an input list, as per the documentation [104]. On that list were appended model priors, as per the example presented below.

$logbkfrac$ is an estimate for the initial depletion level of the stock, which was set tentatively at 0.8. $logn$ corresponds to the p parameter in the modified Pella-Tomlinson formulation, which was set to 2 to match Schaefer's production model. This was chosen in order to approximate the output to those available from the previous methods. $logalpha$ and $logbeta$ represent the settings for α and β, which are a reparameterization of ratio between the process the observation and process errors [69]:

$$\alpha = \frac{\sigma_I}{\sigma_B} \quad \text{and} \quad \frac{\sigma_C}{\sigma_F} \tag{3.2}$$

In the situation where observation error from I or C can not be separated from the process error B or F, a possible simplification is to assume they are equal. Setting these ratios to 1 enforces this choice on the model [69].

```
modelo_spict$priors$logbkfrac <- c(log(0.8),0.5,1)
modelo_spict$ini$logn <- log(2) #adjust production curve to Shaefer
modelo_spict$phases$logn <- -1
modelo_spict$priors$logalpha <- c(1, 1, 0)
modelo_spict$priors$logbeta <- c(1, 1, 0)
```

From this point, the model is fit through a single function, *fit.spict()* which does not require any additional parameters. All plots were rendered with *SPiCT*'s extensive built-in methods for plotting, which can be rendered either into predefined panels or individual plots. For added flexibility, individual plots were created for this work, assembled in user-defined panels.

SPiCT was incorporated in the *Shiny* app with user choices for priors and some plots and value boxes in the output. The structure used in the analysis was transposed to the app without significant alterations.

3.2.4 CatDyn

In order to apply the complete hierarchical framework enabled by *CatDyn*, each year of the time series would require to have the catch dynamic model fit individually. *CatDyn*'s function that performs the reconstruction of the series through back-calculation requires a minimum of 15 fishing seasons [80].

While catch and effort data available for this work spans 28 years, octopus mean-weight data for each week in the entire series would be required to convert catch weight into number of individuals. Despite such data was being collected under the Portuguese *DCF*, at the time of this work a complete series spanning 15 years was not available. This unfortunately prevents the application of the complete framework.

As an illustration of the depletion model as it is implemented by *CatDyn*, the *GDM* was fit to the last fishing season of the polyvalent fleet in both Western and Southern regions of Portugal. As it was defined in previous works concerning the Portuguese octopus fishery, the fishing season was considered to have started at 1 of January [105]. Therefore, the 2 fishing seasons presented correspond to data from the year 2022 in both regions.

Data for the mean body weight of octopus individuals at each week is necessary in order to convert landing weights into estimates for number of individuals. Data from auction market sampling under the Portuguese *DCF* was used for this purpose. Mean body weight for the samples was calculated for each week and region and estimates were aggregated to the catch-effort dataset.

In order to determine the presence of recruitment and catch spikes, data was converted into *CatDyn*'s custom class *CatDynData()* and the catch statistic was calculated, for each point of the series, through the *plot()* method for the class *CatDynData()* that is added by the package. Local *maxima* and *minima* were selected as candidates for the occurrence of such pulses.

In the context of an octopus fishery, abundance pulses are expected to be associated with either an influx from recruitment or the leaving of spawning females from the fishery [32]. In a previous application of this method to the octopus fishery in Asturias, the hypothesis of females becoming unavailable to the fishery due to behaviour changes caused by spawning was accepted since egg-carrying females do not engage with type of traps employed in Asturias [32]. In Portuguese fisheries, both pots and traps are used on the the octopus fishery and octopus females will not avoid using pots as shelter while spawning. Preliminary analysis of biological sampling data of octopus sex-ratios variation by week (Appendix B), which was conducted for *WGCEPH 2023* [106] did not indicate a decrease on females proportion on the catch. For these reasons, it was assumed that, unlike what happens in the Asturias fishery, spawning females cannot be assumed to become unavailable for the fishery.

In *CatDyn*, catch spike events are encoded by the package as a list of time step indexes. A parameter p regarding the number of observed perturbations must be specified by the user, with negative values being used in the case of emigration events [80]. In this work, p was set to positive values.

While *CatDyn* supports several distributions and optimizers, the choices for this work were restricted mostly to choices employed in the Asturias application of this method [32]. Tested distributions were negative binomial, normal, lognormal and gamma. Optimizers considered were, as passed to *R*'s function *optimx()*: 'CG','spg','BFGS' and 'Nelder-Mead' [107]. In this approach, each set of perturbation indexes is tested with 16 combinations of distributions and optimizers.

In order to expedite the fitting process, *CatDyn*'s built-in functions for data ingestion and model fitting were wrapped in a custom function for performing trials which allows for the specification of all priors and hyperparameters in a single pass. Compared to previous methods, *CatDyn* is extremely sensitive to prior specifications and the optimizer methods employed, so trial and error was necessary until a stable set of priors was achieved to bypass immediate convergence failure and begin to fine-tune the fitting process. The settings used for the comparisons are as illustrated in the example below:

```
fit_w_22_1 =
  trialer(cat_w_22,
```

```
    p = 1,
    M = 1/52,
    N0.ini = 15000,
    P.ini = list(1000),
    k.ini = 0.01,
    alpha.ini = 0.5,
    beta.ini  = 0.5,
    P = list(43),
    distr = 'negbin',
    method = 'CG',
    itnmax = 100000,
    disp = 50)
```

For each region, the best model was chosen after fits with implausible estimates were excluded, such as those which result in estimates for M, natural mortality, larger than 0.1 or smaller than 0.01 [32]. The best fit was then selected manually from the remaining models by examining the correlation matrix of parameter estimates and selecting the model with the least correlated estimates (≈ 0).

Considering the amount of manual intervention and oversight required by the user, performance times were not measured for *CatDyn*. The fitting process for the 2022 fishing seasons were incorporated into the *Shiny* app for experimentation, but the full framework would require a complete series to be available.

The results obtained through the approach described above are reported in the following section. After a brief examination of the time series that served as the basis of the analysis, the estimates obtained with each methodology are presented in the same order that has been used so far. Performance of each tool is also reported on.

Chapter 4

Results

4.1 Landings data

After removal of data referring to purse seine fishing trips, available data for this work consisted of 8 310 659 fishing trips for the Western and Southern coasts of continental Portugal between 1995 and 2022. Based on the distributions of octopus proportion in each landing (Figure 4.1), it was decided to cutoff the average weight octopus in each vessel's landings at 0.5 in order to restrict the polyvalent fleet to vessels that actually target the species.

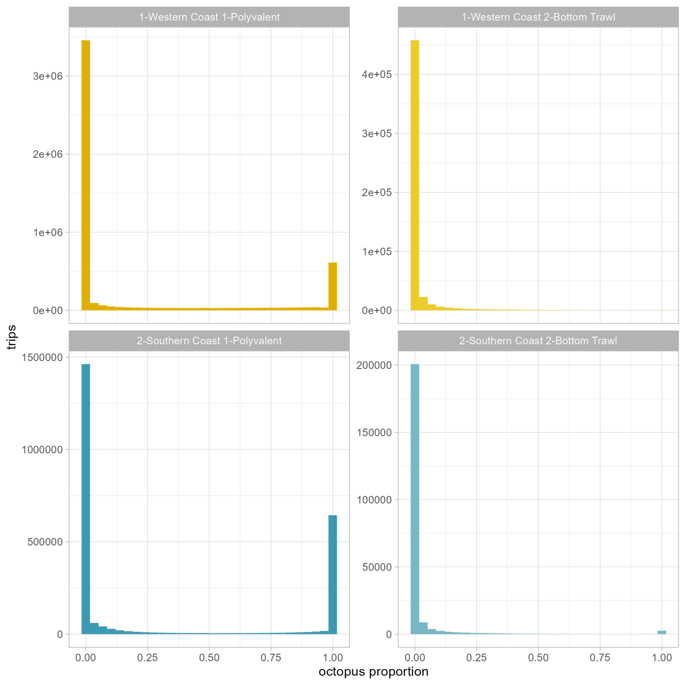


FIGURE 4.1: Proportion of octopus landings in each fish trip, for the bottom trawl and polyvalent fleets in the Southern and Western coasts of Portugal.

Upon removal of vessels less likely to engage on the octopus fishery, 1 926 219 trips remained (23.18% of the previous total), which were considered for this work. A summary of their distribution by region, year and fishing gear is presented on Figure 4.2. The final dataset consisted of 896 986 trips from the polyvalent fleet in the Western region (46.57% of the total), 750 427 trips from the polyvalent fleet in the Southern region (38.96% of the total), 176 925 trips from the bottom trawl fleet in the Western region (9.18% of the total) and 101 881 trips from bottom trawl fleet in the Southern region (5.29% of the total). Even after the removal of trips assumed not to be targeting octopus, the polyvalent fishery is where most of the fishing effort towards octopus happens.

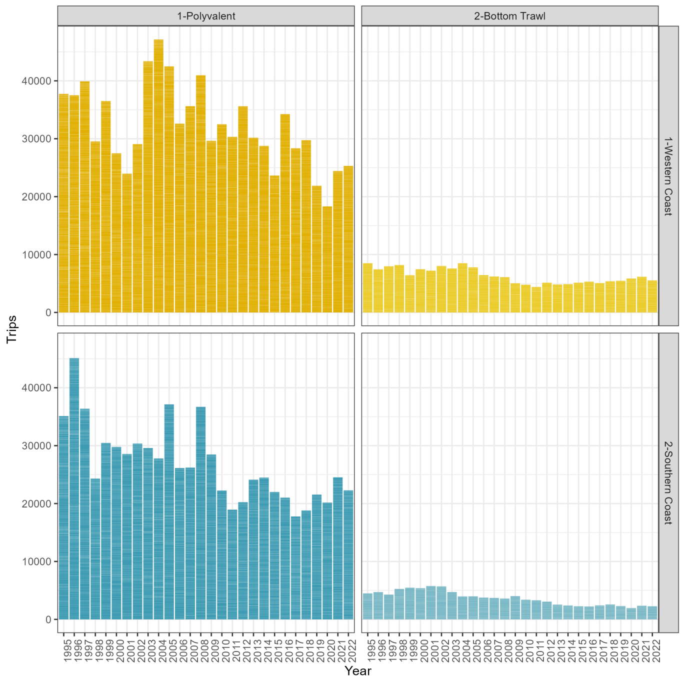


FIGURE 4.2: Number of trips considered for this study, by fishing gear (bottom trawl and polyvalent), region (Southern and Western coasts of Portugal) and year (1995-2022).

There is a slight downward trend in the fishing effort for all gears and regions. In recent years, for both the western and southern regions the polyvalent fleet has stabilized around 25 000 trips, where the bottom trawl fleet ranges between around 5 000 trips in the Western region and 3 000 trips in the Southern region.

In the considered time period of 1995-2022, octopus landings in the polyvalent fleet reached their maximum of over 4 000 tons in 2016 in the Western region. In the Southern region, the maximum occurred earlier, with the highest landings of over 3 000 tons being registered in the years of 2005 and 2008 (Figure 4.3). In later years, yearly landings have fallen to 1990-2000 levels. Both series appear to be stationary in trend, with the oscillations following a cyclical pattern with shifts in variance, rather than long term shifts in abundance.

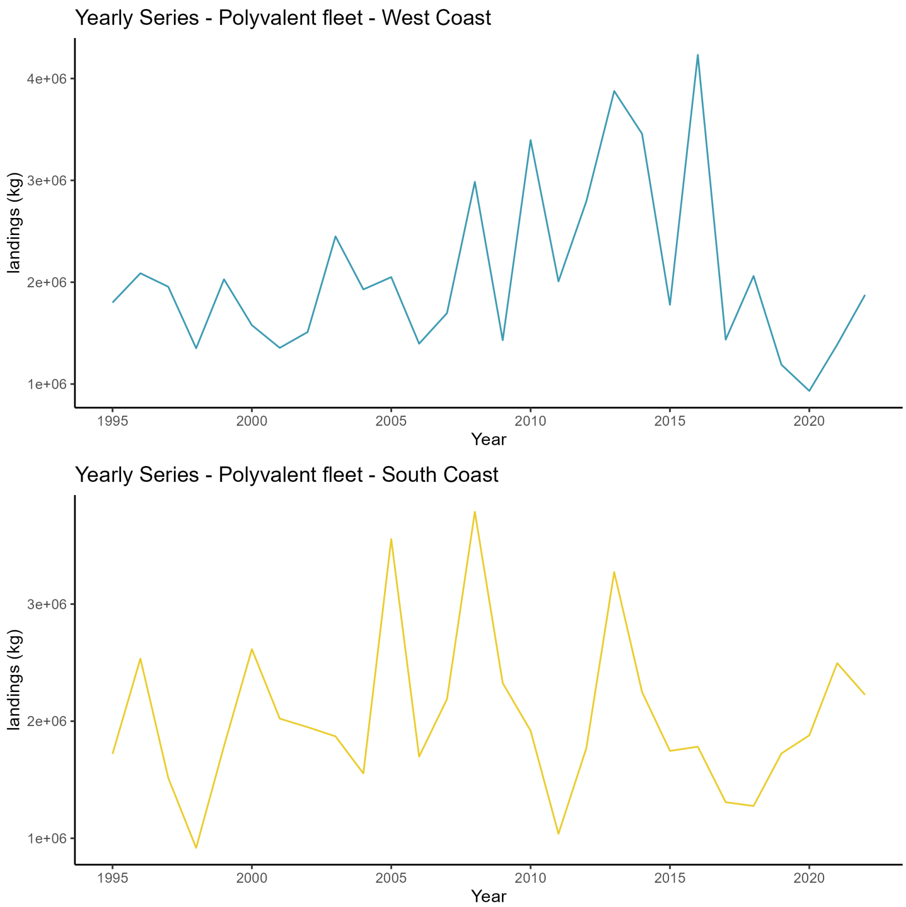


FIGURE 4.3: Yearly octopus landings from the polyvalent fleet in the Western (top) and Southern (bottom) regions of Portugal.

The octopus landings from polyvalent fleet were aggregated into both yearly (Figure 4.3) and weekly (Figure 4.4) time series, separated by region. The augmented Dickey-Fuller (ADF) test failed to detect the presence of a unit root on both weekly time series, leading to the alternate hypothesis that they are stationary (Table 4.1).

TABLE 4.1: Results from the ADF and KPSS tests for the presence of unit root in the portuguese octopus landings from the polyvalent fleet.

fleet	p.value	Estationary	Differentiation	S.Diff
Polyvalent Fleet - West Coast - Weeks	0.01	Yes	1.00	0.00
Polyvalent Fleet - South Coast - Weeks	0.01	Yes	0.00	0.00
Polyvalent Fleet - West Coast - Years	0.82	No	0.00	-
Polyvalent Fleet - South Coast - Years	0.16	No	0.00	-

Testing the series with the *forecast::ndiffs()* implementation of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, however, resulted in one differentiation being suggested as necessary in order for the West Polyvalent weekly time series to achieve stationarity. According to the *forecast::nsdiffs()* test, neither series requires seasonal differentiation.

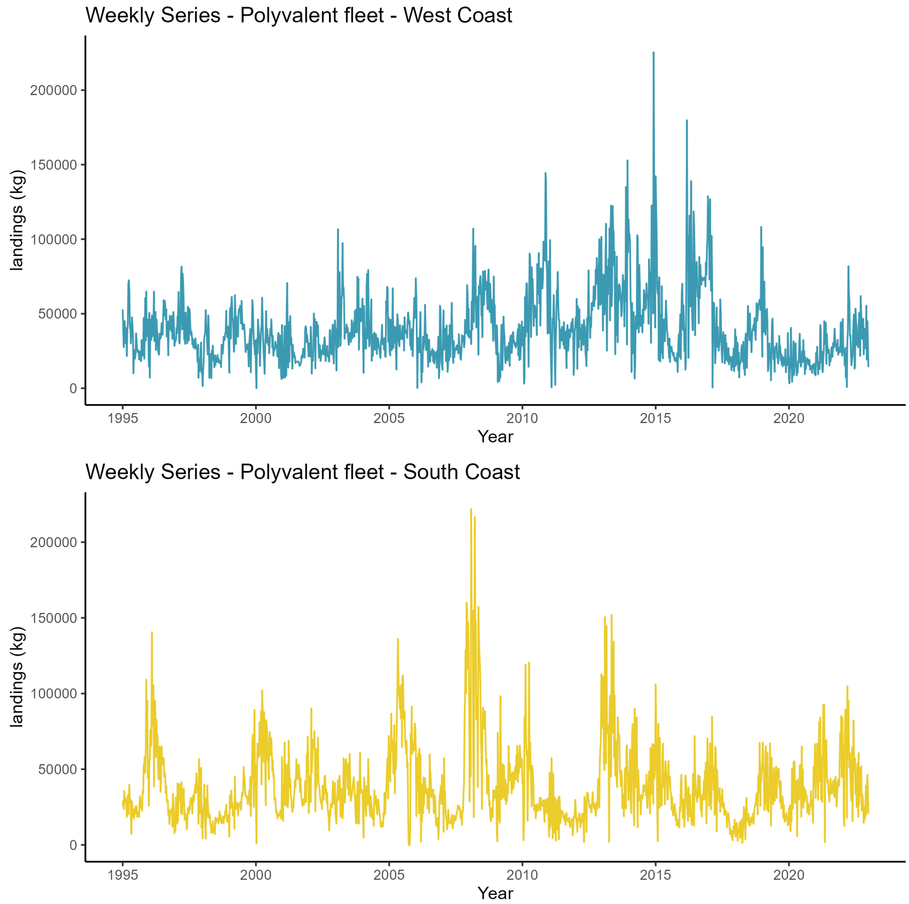


FIGURE 4.4: Weekly octopus landings from the polyvalent fleet in the Western (top) and Southern (bottom) regions of Portugal.

Autocorrelation and partial autorrelation functions (Figure 4.5) indicate that in the Western Region significant autocorrelations are found at lags 2 and 7, with the partial autocorrelation spiking again at lag 12. With the data aggregated at a week time step (Figure 4.6) it become clearer that a multi-year cycle may be present in the data. The regularity of the spikes in partial autocorrelation significance may also indicate the existance of a seasonal autorregressive structure.

Overall, data from the Southern region follows similar patterns, albeit with the significant lag being of 10 years, instead of 2 or 7. The same seasonal autoregressive structure may be inferred from the partial autocorrelations.

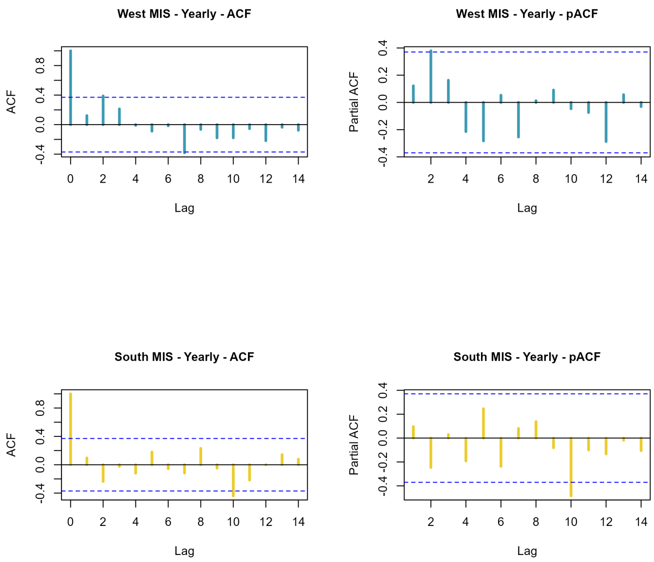


FIGURE 4.5: Autocorrelation Function (ACF) and partial autocorrelation function (pACF) of yearly octopus landings from the polyvalent fleet in the Western (top) and Southern (bottom) regions of Portugal.

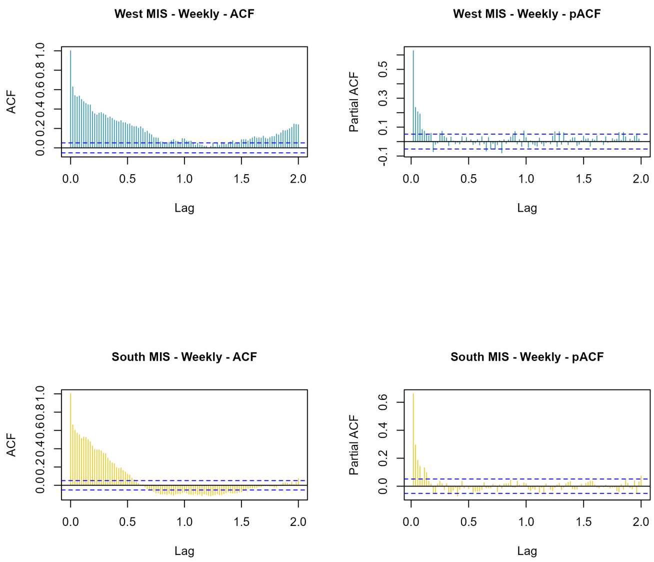


FIGURE 4.6: Autocorrelation Function (ACF) and partial autocorrelation function (pACF) of weekly octopus landings from the polyvalent fleet in the Western (top) and Southern (bottom) regions of Portugal.

The abundance index derived for this fishery was measured in kg/trip, and in both regions it follows a very close pattern to the landings (Figures 4.7 and 4.8). However, standartization approaches (LPUE series through estimation of the Efficiency Power of each fishing gear [95] or through a Generalized Linear Model with a Tweedie distribution [96]) failed to yield usable results. The efficiency approach simply applied a linear transformation to the data and the *GLM* model failed to converge. Due standardization method was unsucessfull, nominal landings per unit of effort (*LPUE*) were used. In both regions, average *LPUE* oscillated between 40 and 120 kg/trip.

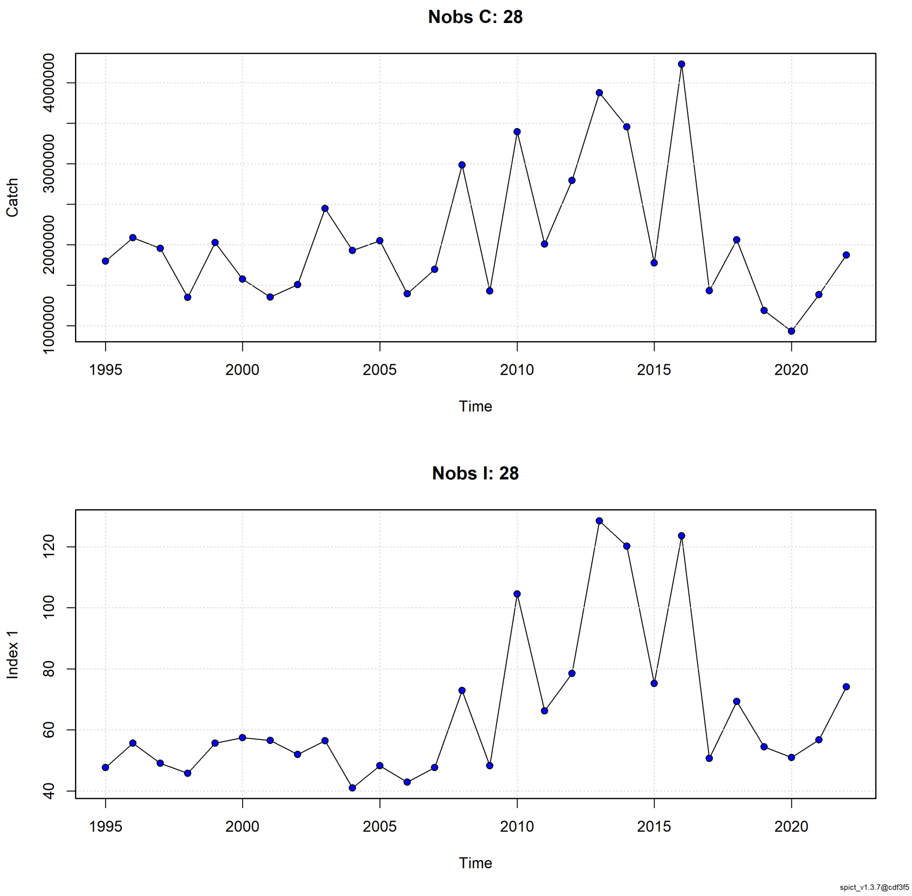


FIGURE 4.7: Octopus catches (kg) and LPUE (Index 1) of the polyvalent fleet in the Portuguese Western Coast between 1995 and 2022, aggregated by year, plotted with built-in SPiCT plotting functions.

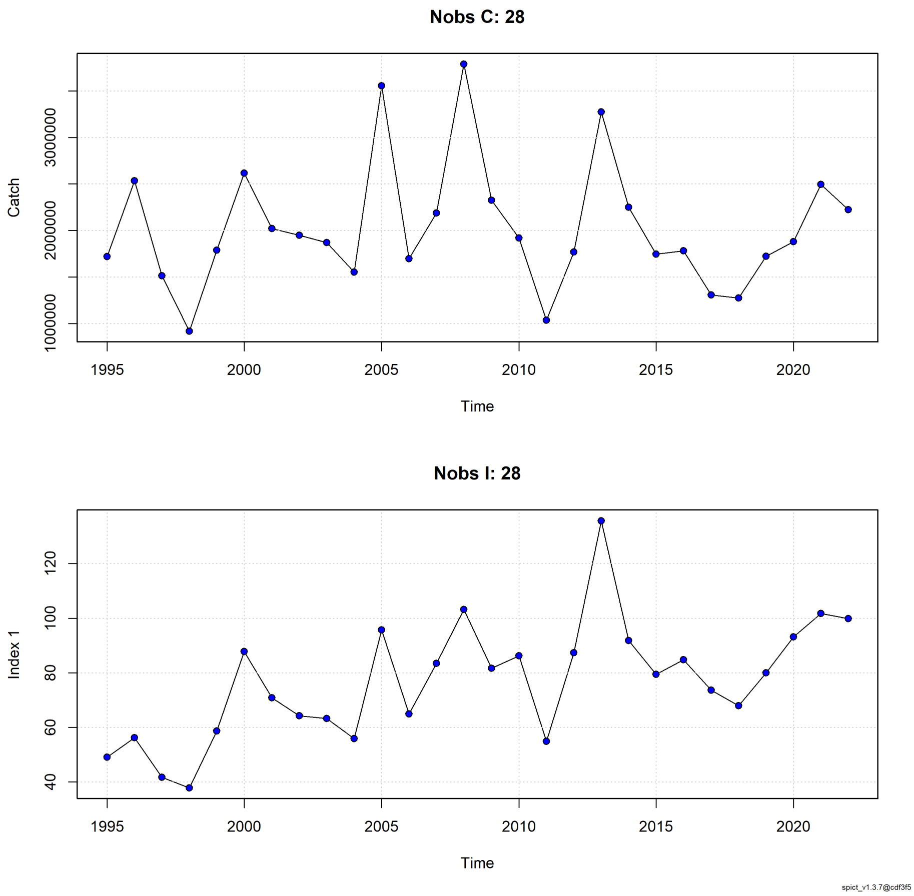


FIGURE 4.8: Octopus catches (kg) and LPUE (Index 1) of the polyvalent fleet in the Portuguese Southern Coast between 1995 and 2022, aggregated by year, plotted with built-in SPiCT plotting functions.

4.2 CMSY++

4.2.1 Octopus stock assessment

Using *CMSY++*, surplus production models were fit successfully to yearly series of octopus landings of the polyvalent fleet in both western and southern regions of Portugal. The package generates a report with separate estimates from the catch-only estimation method (*CMSY*), the Bayesian surplus model (*BSM*). B_{MSY}, F_{MSY}, B/B_{MSY} and F/F_{MSY} estimates reported are based on the *BSM* analysis.

For the western region (Table 4.2), incorporating the abundance index with the *BSM* method resulted in a larger estimate for K (14600 tons vs 130000) and a smaller *MSY* of 2230 tons. Estimates for r were 0.76 and 0.608, which would fall under the expected values for a high-resilience stock [53].

TABLE 4.2: Estimates with 95 % confidence interval from the *CMSY++* model fit to the octopus landings from the polyvalent fleet in the Western region of Portugal between 1995 and 2022. Results presented are from both the catch-only method and the Bayesian surplus production method.

Parameter	units	CMSY	BSM
q	adim.	-	0.426 (0.297-0.611)
r	adim.	0.76 (0.615-0.945)	0.608 (0.426-0.877)
K	1000 tons	13 (10.6-18.5)	14.6 (10.2-21.3)
MSY	1000 tons	2.46 (2.14-2.76)	2.23 (2.01-2.52)
F_{MSY}	adim.	-	0.304 (0.213-0.439)
B_{MSY}	1000 tons	-	7.32 (5.12-10.7)
B/B_{MSY} (2022)	adim	-	0.646 (0.443-0.87)
B/K (2022)	adim.	0.337 (0.161-0.527)	0.337 (0.161-0.527)
F (2022)	adim.	-	0.338 (0.203-0.582)
F/F_{MSY} (2022)	adim.	-	1.11 (0.715-1.92)
Exploitation ($F/r/2$) (2022)	adim.	1.01	1.25

Under these estimates, the fishery is estimated to have entered over-exploitation in 2009, when fishing mortality F rose above the estimated maximum sustainable fishing mortality F_{MSY} (Figure 4.9). As a consequence, estimated stock biomass B fell below the B_{MSY} level from 2011 until 2022.

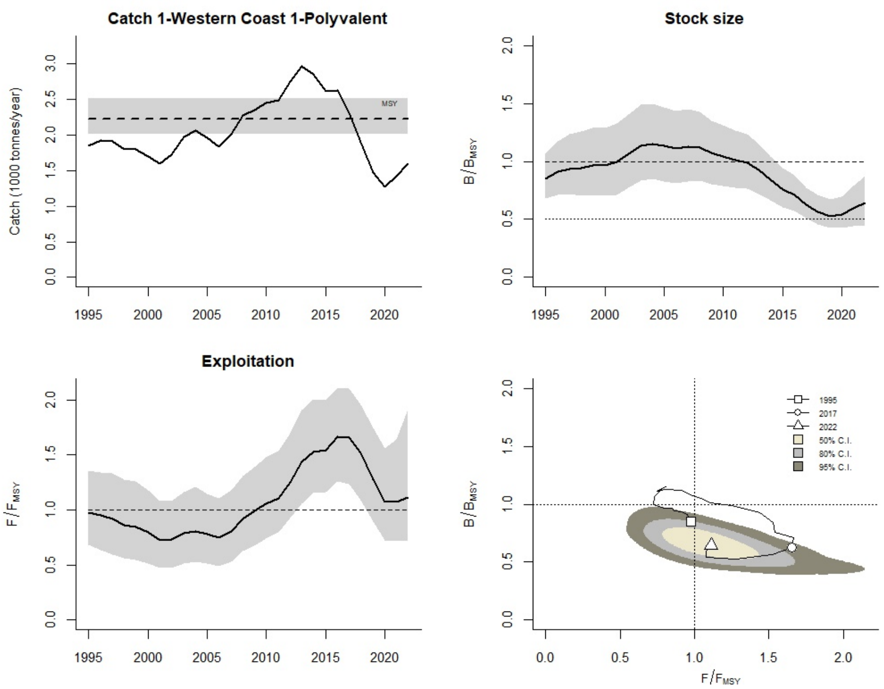


FIGURE 4.9: Results from *CMSY++* model fit or the Portuguese octopus landing by the polyvalent fleet in the Western region of Portugal between 1995 and 2022: yearly catch (top left), MSY estimated biomass relative to the B_{MSY} (top right), estimated fishing mortality relative to the F_{MSY} (bottom left) and stock trajectory in terms of relative fishing mortality and relative biomass (bottom right).

Overall, combining the relative fish mortality and relative biomass trends presented

presented in a Kobe plot (Figure 4.10), this model fit presents a stock that, after reaching a healthy status in 2002 has been consistently overfished, to the point where its biomass has fallen below sustainable levels in order to maintain equilibrium between production and depletion.

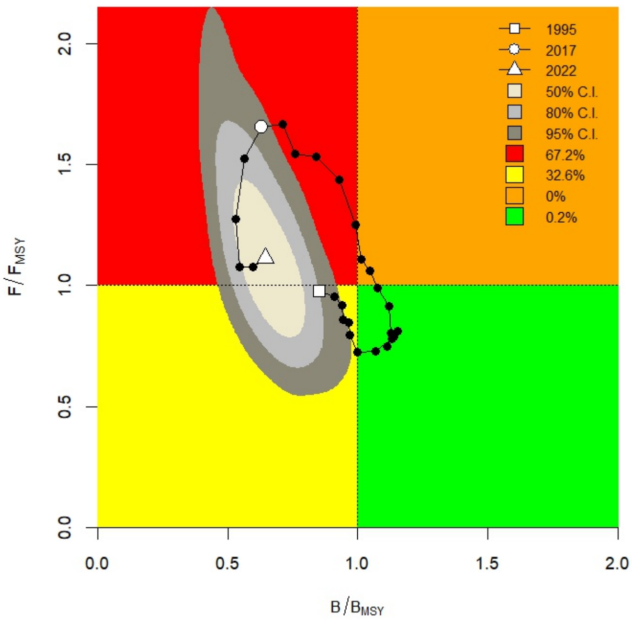


FIGURE 4.10: Results from *CMSY++* model fit for the Western octopus fishery by the polyvalent fleet in Portugal: Kobe plot for the trajectory of the estimated relation between relative fishing mortality and relative biomass.

In the Southern region, a similar scenario is obtained from applying *CMSY++* (Table 4.3). The estimates for carrying capacity K range from 11800 tons (*CMSY*) to 12000 tons *BSM* and the estimate for *MSY* is between 2230 tons/year (*CMSY*) and 2140 tons/year (*BSM*).

The trends for relative biomass and relative fishing mortality (Figure 4.11) are similar to those from the Western region, albeit starting earlier, in 2005. The overall trajectory of the stock appears to be one of rising fishing mortality, well above F_{MSY} levels and decreasing biomass (Figure 4.12).

TABLE 4.3: Estimates with 95 % confidence interval from the *CMSY*++ model fit to the octopus landings from the polyvalent fleet in the Southern region of Portugal between 1995 and 2022. Results presented are from both the catch-only method and the Bayesian surplus production method.

Parameter	units	CMSY	BSM
q	adim.	-	0.468 (0.329-0.638)
r	adim.	0.76 (0.527-0.959)	0.710 (0.482-1)
K	1000 tons	11.8 (9.14-17.5)	12 (8.53-18.1)
MSY	1000 tons	2.23 (2-2.52)	2.14 (1.96-2.38)
F_{MSY}	adim.	-	0.355 (0.241-0.502)
B_{MSY}	1000 tons	-	6.01 (4.27-9.06)
B/B_{MSY} (2022)	adim	-	0.612 (0.447-0.834)
B/K (2022)	adim.	0.404 (0.249-0.577)	0.404 (0.249-0.577)
F (2022)	adim.	-	0.62 (0.369-0.978)
F/F_{MSY} (2022)	adim.	-	1.74 (1.12-2.81)
Exploitation ($F/r/2$) (2022)	adim.	1.22	1.29

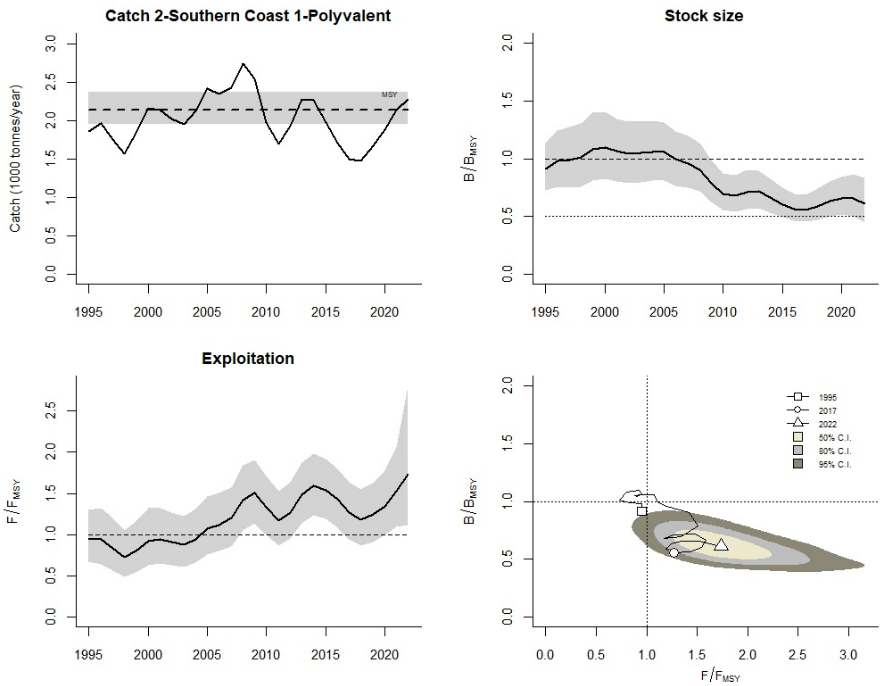


FIGURE 4.11: Results from CMSY++ model fit for the Portuguese octopus landing by the polyvalent fleet in the Southern region of Portugal between 1995 and 2022: yearly catch (top left), MSY estimated biomass relative to the B_{MSY} (top right), estimated fishing mortality relative to the F_{MSY} (bottom left) and stock trajectory in terms of relative fishing mortality and relative biomass (bottom right).

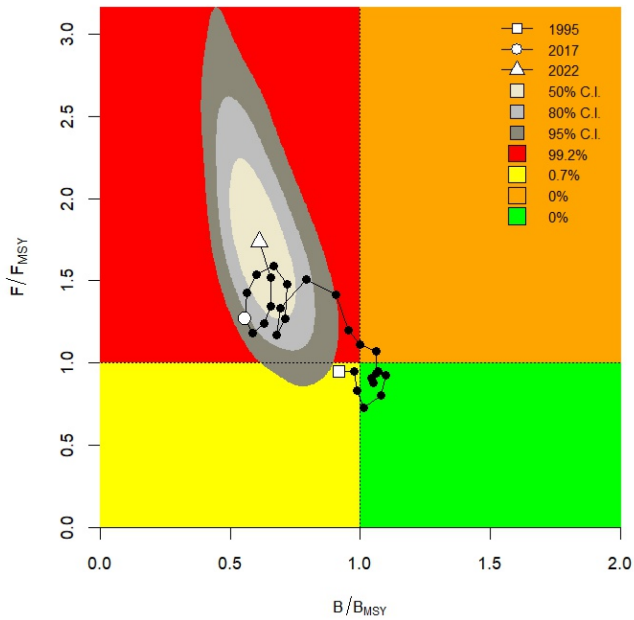


FIGURE 4.12: Results from CMSY++ model fit for the Southern octopus fishery by the polyvalent fleet in Portugal: Kobe plot for the trajectory of the estimated relation between relative fishing mortality and relative biomass.

4.2.2 Method evaluation

Performance times for preprocessing the data, fitting the models and rendering the outputs are presented on Table 4.4. It should be noted that the script execution is extremely verbose and induced severe delay on the response of the *IDE* (in this case, *RSTUDIO*). The recorded times refer to the end of the calculations and disk storage of the outputs, but the user experience will result in delays of over 15 minutes above the recorded times.

Preprocessing was a trivial task, as far as computations go, consisting of rearranging vectors into new dataframes. Fitting the models was achieved in very short times. The most onerous step was rendering the outputs, due to all instructions being nested in several *for()* structures and the creation of the automated report.

TABLE 4.4: Run times for *CMSY++* fitting by source data) and time spent (seconds) in each process phase (pre-process, modelling fit and render of outputs).

Framework	Phase	Time
CMSY++ - Polyvalent, Western Coast, Yearly data	Pre.process	0.93
CMSY++ - Polyvalent, Southern Coast, Yearly data	Pre.process	1.96
CMSY++ - Polyvalent, Western Coast, Yearly data	Model.fit	67.72
CMSY++ - Polyvalent, Southern Coast, Yearly data	Model.fit	69.20
CMSY++ - Polyvalent, Western Coast, Yearly data	Output.Render	244.08
CMSY++ - Polyvalent, Southern Coast, Yearly data	Output.Render	258.93

4.3 JABBA

4.3.1 Octopus stock assessment

Using *JABBA* with three different models specifications (Schaefer, Pella-Tomlinson and Fox), estimates for the octopus polyvalent fishery in the Western region are presented in Table 4.5. Results from the Schaefer formulation are presented in the body of this section, whereas results from the Pella-Tomlinson and Fox formulations have been included in Appendix C.

All three models presented similar results for the status of the stock, with the largest discrepancy being in the estimation of the carrying capacity, which ranged from $K = 531418.2$ tons in the Fox model to $K = 70327.2$ tons in the Schaefer model. Even the more conservative estimates from Fox's formulation is considerably higher than the $K = 130000$ tons estimated by *CMSY++*. Despite the differences in estimated carrying capacities, all models estimated similar values for MSY, ranging between 4047 tons (Schaefer) and 4838 tons (Fox). All 3 models estimated the proportion of biomass to the carrying capacity in the last year of the series ($P28$) to above 80% of carrying capacity.

Overall, all scenarios presents a much larger stock, much less impacted by the fishery. Fishing mortality is estimated to have never risen above 30% of F_{MSY}, where biomass is estimated to always have remained comfortably above the estimated sustainable level (Figures 4.13, C.1, C.2). The Kobe plot for all three models are very similar, drawing a very positive assessment of the stocks.

TABLE 4.5: *JABBA* estimates for the octopus polyvalent fishery in the Portuguese Western Coast with lower confidence interval (lci) and upper confidence interval (uci), for three *SPM* formulations: Schaefer, Pella-Tomlinson and Fox.

var	model	mu	lci	uci
K	Schaefer	70327225.75	26408576.40	220913937.79
K	Pella-Tomlinson	61978511.39	29877606.10	194742446.80
K	Fox	53418235.38	24646488.00	144307619.29
r	Schaefer	0.24	0.10	0.64
r	Pella-Tomlinson	0.23	0.10	0.61
r	Fox	0.23	0.10	0.54
psi	Schaefer	0.79	0.54	1.17
psi	Pella-Tomlinson	0.77	0.51	1.17
psi	Fox	0.79	0.52	1.19
sigma.proc	Schaefer	0.06	0.04	0.10
sigma.proc	Pella-Tomlinson	0.06	0.03	0.10
sigma.proc	Fox	0.06	0.04	0.10
m	Schaefer	2.00	2.00	2.00
m	Pella-Tomlinson	1.19	1.19	1.19
m	Fox	1.00	1.00	1.00
Hmsy	Schaefer	0.12	0.05	0.32
Hmsy	Pella-Tomlinson	0.19	0.08	0.52
Hmsy	Fox	0.23	0.10	0.54
SBmsy	Schaefer	35163612.88	13204288.20	110456968.89
SBmsy	Pella-Tomlinson	24790275.34	11950498.08	77893430.61
SBmsy	Fox	19661292.22	9071467.81	53114339.19
MSY	Schaefer	4047218.29	1971427.62	12559421.18
MSY	Pella-Tomlinson	4837835.00	2160946.27	16600235.43
MSY	Fox	4483774.52	2237414.45	13385854.37
bmsyk	Schaefer	0.50	0.50	0.50
bmsyk	Pella-Tomlinson	0.40	0.40	0.40
bmsyk	Fox	0.37	0.37	0.37
P1	Schaefer	0.79	0.54	1.18
P1	Pella-Tomlinson	0.76	0.50	1.16
P1	Fox	0.78	0.51	1.18
P28	Schaefer	0.88	0.63	1.07
P28	Pella-Tomlinson	0.87	0.60	1.06
P28	Fox	0.84	0.60	1.05
B_Bmsy.cur	Schaefer	1.76	1.26	2.15
B_Bmsy.cur	Pella-Tomlinson	2.18	1.50	2.65
B_Bmsy.cur	Fox	2.29	1.64	2.86
H_Hmsy.cur	Schaefer	0.26	0.08	0.70
H_Hmsy.cur	Pella-Tomlinson	0.18	0.04	0.54
H_Hmsy.cur	Fox	0.18	0.05	0.49

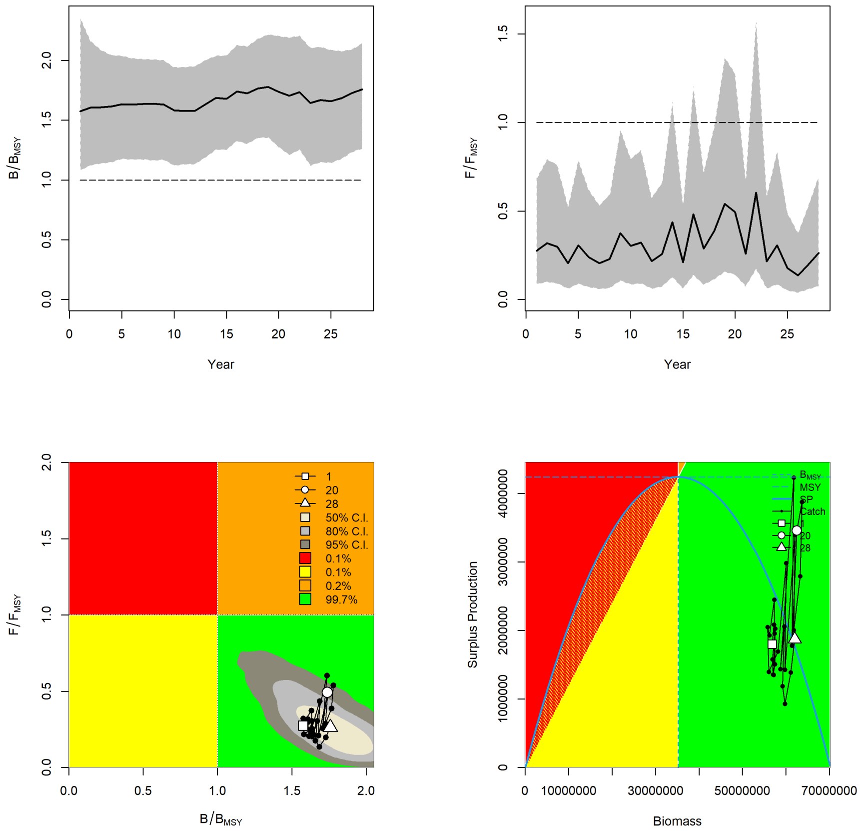


FIGURE 4.13: JABBA surplus production model (Schaefer) fit for the octopus polyvalent fishery in the Portuguese Western Coast: yearly biomass estimates relative to the estimate for the B_{MSY} estimate (top left), yearly fishing mortality relative to the estimate for the F_{MSY} estimate (top right), Kobe plot (bottom left) and surplus production curve (bottom right).

As for the octopus fishery in the Southern region, differences between the model formulations were more accentuated (Table 4.6). The estimate for K in Pella-Tomlinson's model of 17957 tons was less than half of the estimate obtained with Schaefer's model (46340 tons). Differences in MSY estimates were also wider, from 2537 tons (Schaefer) to 3459 tons (Pella-Tomlinson). Overall, the model following Fox's formulation produced estimates that were intermediate when compared to the other 2. All models estimated the growth coefficient r to be significantly lesser (0.31 - 0.45) than the prior offered, which suggests that the stock dynamic that is being modelled is less resilient that it was anticipated.

Overall the trajectory and status assessment are much more positive than the fit obtained with *CMSY++* (Figures 4.14, C.3, C.4). Despite all models estimating the starting

TABLE 4.6: JABBA estimates for the octopus polyvalent fishery in the Portuguese Southern Coast with lower confidence interval (lci) and upper confidence interval (uci), for three *SPM* formulations: Schaefer, Pella-Tomlinson and Fox.

var	model	mu	lci	uci
K	Schaefer	46339871.86	24548861.62	70451272.33
K	Pella-Tomlinson	17957350.65	11070354.97	34714663.28
K	Fox	22239538.22	15198219.94	30688153.80
r	Schaefer	0.31	0.12	0.60
r	Pella-Tomlinson	0.45	0.21	0.69
r	Fox	0.37	0.20	0.59
psi	Schaefer	0.62	0.42	0.90
psi	Pella-Tomlinson	0.58	0.41	0.85
psi	Fox	0.61	0.43	0.88
sigma.proc	Schaefer	0.18	0.14	0.21
sigma.proc	Pella-Tomlinson	0.17	0.13	0.21
sigma.proc	Fox	0.18	0.14	0.21
m	Schaefer	2.00	2.00	2.00
m	Pella-Tomlinson	1.19	1.19	1.19
m	Fox	1.00	1.00	1.00
Hmsy	Schaefer	0.15	0.06	0.30
Hmsy	Pella-Tomlinson	0.38	0.18	0.58
Hmsy	Fox	0.37	0.20	0.59
SBmsy	Schaefer	23169935.93	12274430.81	35225636.16
SBmsy	Pella-Tomlinson	7182613.09	4427940.29	13885232.83
SBmsy	Fox	8185557.92	5593907.05	11295183.29
MSY	Schaefer	3459306.14	1577168.81	6575830.66
MSY	Pella-Tomlinson	2537009.97	1758635.53	4362633.59
MSY	Fox	2996824.18	1779074.67	4770420.08
bmsyk	Schaefer	0.50	0.50	0.50
bmsyk	Pella-Tomlinson	0.40	0.40	0.40
bmsyk	Fox	0.37	0.37	0.37
P1	Schaefer	0.50	0.33	0.72
P1	Pella-Tomlinson	0.47	0.34	0.67
P1	Fox	0.50	0.36	0.71
P28	Schaefer	0.97	0.65	1.16
P28	Pella-Tomlinson	0.84	0.67	1.11
P28	Fox	0.93	0.72	1.10
B_Bmsy.cur	Schaefer	1.95	1.29	2.32
B_Bmsy.cur	Pella-Tomlinson	2.10	1.68	2.77
B_Bmsy.cur	Fox	2.54	1.97	3.00
H_Hmsy.cur	Schaefer	0.35	0.16	0.85
H_Hmsy.cur	Pella-Tomlinson	0.42	0.20	0.67
H_Hmsy.cur	Fox	0.29	0.17	0.55

biomass to be close to $0.5K$ (with Fox' model estimating it to be below, at $0.47K$), all models plot a similar trajectory that rises confortably above B/B_{MSY} with fishing mortality safely below F/F_{MSY}.

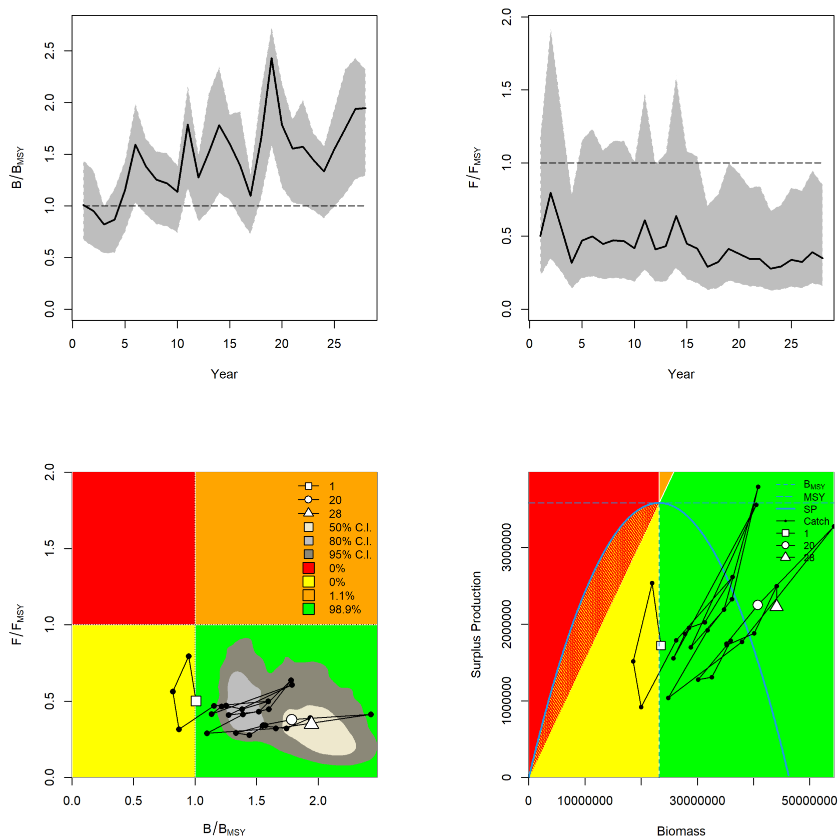


FIGURE 4.14: JABBA surplus production model (Schaefer) fit for the octopus polyvalent fishery in the Portuguese Southern Coast: yearly biomass estimates relative to the estimate for the BMSY estimate (top left), yearly fishing mortality relative to the estimate for the FMSY estimate (top right), Kobe plot (bottom left) and surplus production curve (bottom right).

4.3.2 Method evaluation

Despite most of the documentation guiding the user, towards the use of a prime script that is meant to be customized before being ran as a whole, *JABBA*'s built-in functions are enough to streamline the task of model fitting. They could be easily incorporated into a wrapper function in order to run and store results of several fits in sequence. *JABBA* itself is prepared to accommodate that functionality through the vectorization of the 'Scenario' parameter in the *build_jabba()* function, but that approach may prove to be too restrictive in some applications.

Priors and hyperparameters are all set in a single function, whose output is then used in the fitting function. Each plot can be produced via its own function, making the outputs accessible and editable. All plots are made with base *R*. Performance times (Table 4.7) are consitent between model formulations and overall are lower than *CMSY++*, which is consistent with the fact that *JABBA* does not use the neural network predictions that *CMSY++* does and its outputs are a lot more granular. The choice of plots for this work was less exhaustive than the defaults that are imposed by *CMSY++*.

TABLE 4.7: Run times for *JABBA* fitting by model type, method (different source data) and time spend (seconds) in each process phase (pre-process, modelling fit and render of outputs).

Model	Framework	variable	value
Schaefer	JABBA - Polyvalent, Western Coast, Yearly data	Pre.process	0.11
Pella-Tomlinson	JABBA - Polyvalent, Western Coast, Yearly data	Pre.process	0.11
Fox	JABBA - Polyvalent, Western Coast, Yearly data	Pre.process	0.11
Schaefer	JABBA - Polyvalent, Southern Coast, Yearly data	Pre.process	0.24
Pella-Tomlinson	JABBA - Polyvalent, Southern Coast, Yearly data	Pre.process	0.26
Fox	JABBA - Polyvalent, Southern Coast, Yearly data	Pre.process	0.26
Schaefer	JABBA - Polyvalent, Western Coast, Yearly data	Model.fit	14.51
Pella-Tomlinson	JABBA - Polyvalent, Western Coast, Yearly data	Model.fit	12.30
Fox	JABBA - Polyvalent, Western Coast, Yearly data	Model.fit	12.47
Schaefer	JABBA - Polyvalent, Southern Coast, Yearly data	Model.fit	13.11
Pella-Tomlinson	JABBA - Polyvalent, Southern Coast, Yearly data	Model.fit	13.48
Fox	JABBA - Polyvalent, Southern Coast, Yearly data	Model.fit	12.63
Schaefer	JABBA - Polyvalent, Western Coast, Yearly data	Output.Render	8.03
Pella-Tomlinson	JABBA - Polyvalent, Western Coast, Yearly data	Output.Render	8.30
Fox	JABBA - Polyvalent, Western Coast, Yearly data	Output.Render	7.45
Schaefer	JABBA - Polyvalent, Southern Coast, Yearly data	Output.Render	11.21
Pella-Tomlinson	JABBA - Polyvalent, Southern Coast, Yearly data	Output.Render	9.23
Fox	JABBA - Polyvalent, Southern Coast, Yearly data	Output.Render	8.24

4.4 SPiCT

4.4.1 Octopus stock assessment

Even though *SPiCT* supports data aggregated to shorter time steps than year, attempts to fit models to data aggregated to weeks or months proved unsuccessful, despite several combinations of prior and configurations being tested. As such, only the results from the fits performed on the yearly data are presented. The results for fitting a surplus production model with *SPiCT* to the polyvalent fishery of octopus in the Western region of Portugal are presented in Table 4.8. Results were remarkably different from the previous frameworks, with the estimate for K being of 12000 tons and the MSY being 7759 tons. Confidence intervals for these estimates are massive, which almost ensures that this fit is inappropriate for describing the status of the octopus stock.

With a MSY that is nearly the triple of the yearly catch of the latter years of the series, the status assessment of the stock is therefore extremely optimistic (Figure 4.15). Relative

TABLE 4.8: Parameter estimates from the SPiCT model fit to the octopus landings from the polyvalent fleet in the Western region of Portugal, in terms of estimates (estimate and log.est), lower confidence interval (cilow) and upper confidence interval (ciupp).

parameter	estimate	cilow	ciupp	log.est
alpha	0.97	0.28	3.37	-0.03
beta	6.50	0.97	43.52	1.87
r	0.29	0.05	1.65	-1.24
rc	0.29	0.05	1.65	-1.24
rold	0.29	0.05	1.65	-1.24
m	8734098.77	8230.07	9268993648.14	15.98
K	120160520.83	51497.93	280371486457.37	18.60
q	0.00	0.00	0.00	-14.28
sdb	0.19	0.08	0.46	-1.67
sdf	0.04	0.01	0.27	-3.14
sdi	0.18	0.11	0.30	-1.70
sdc	0.28	0.20	0.39	-1.27
Bmsys	55798388.50	24842.77	125326620860.94	17.84
Fmsys	0.14	0.02	0.80	-1.99
MSYs	7579645.54	7751.04	7412040913.40	15.84

biomass oscilates between 1.5 and 3 times the B_{MSY} level, with fishing mortality on a downward trending failing to rise above 20% of the reference fishing mortality.

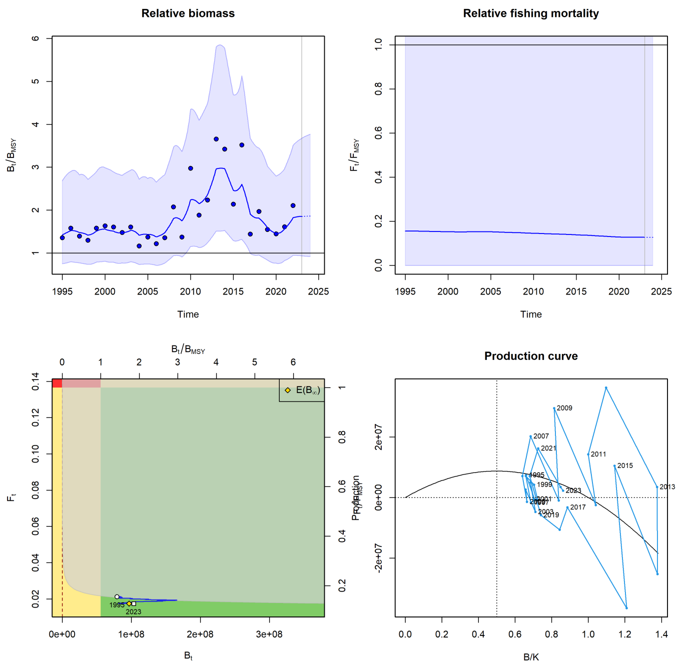


FIGURE 4.15: Results from SPiCT model fit to the octopus fishery from the polyvalent fleet in the Portuguese Western Coast between 1995 and 2022, aggregated by year: estimated biomass over BMSY (top left), estimated fishing mortality over FMSY (top right), Kobe plot with the fishing mortality vs biomass trajectory (bottom left) and surplus production curve with trajectory (bottom right).

The retrospective plots do show that this model is resilient to removal of the more recent years of the series, keeping the consistency of the estimates (Figure 4.16). Mohn's ρ for both B/B_{MSY} and F/F_{MSY} fall between the range of -0.15 and 0.22, which is expected for short-lived species [108]. However, confidence intervals of the retrospective analysis indicate that the accuracy of the estimates can not be relied upon. Model residuals presented no evidence for serial autocorrelation under Ljung-Box test nor appear to significantly deviate from normality (Figure 4.17).

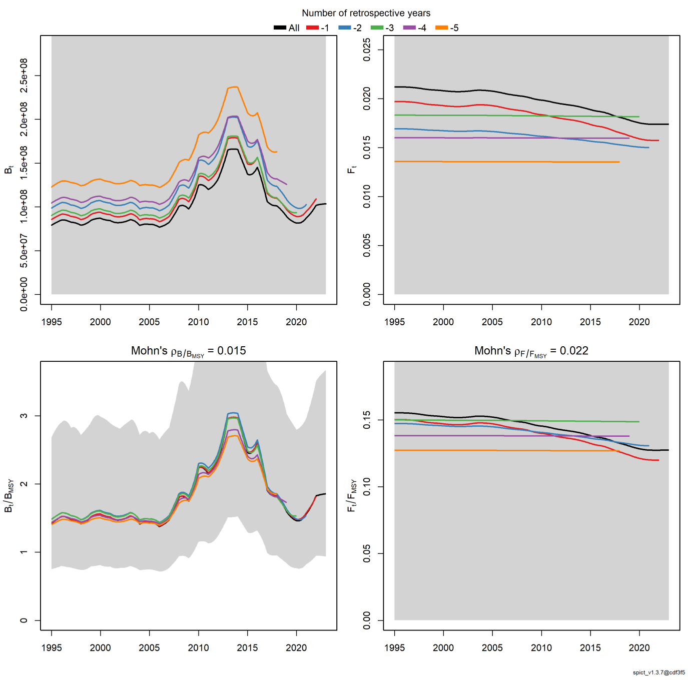


FIGURE 4.16: Retrospective plots for the SPiCT model fit of the octopus fishery from the polyvalent fleet in the Portuguese Western Coast between 1995 and 2022, aggregated by year.

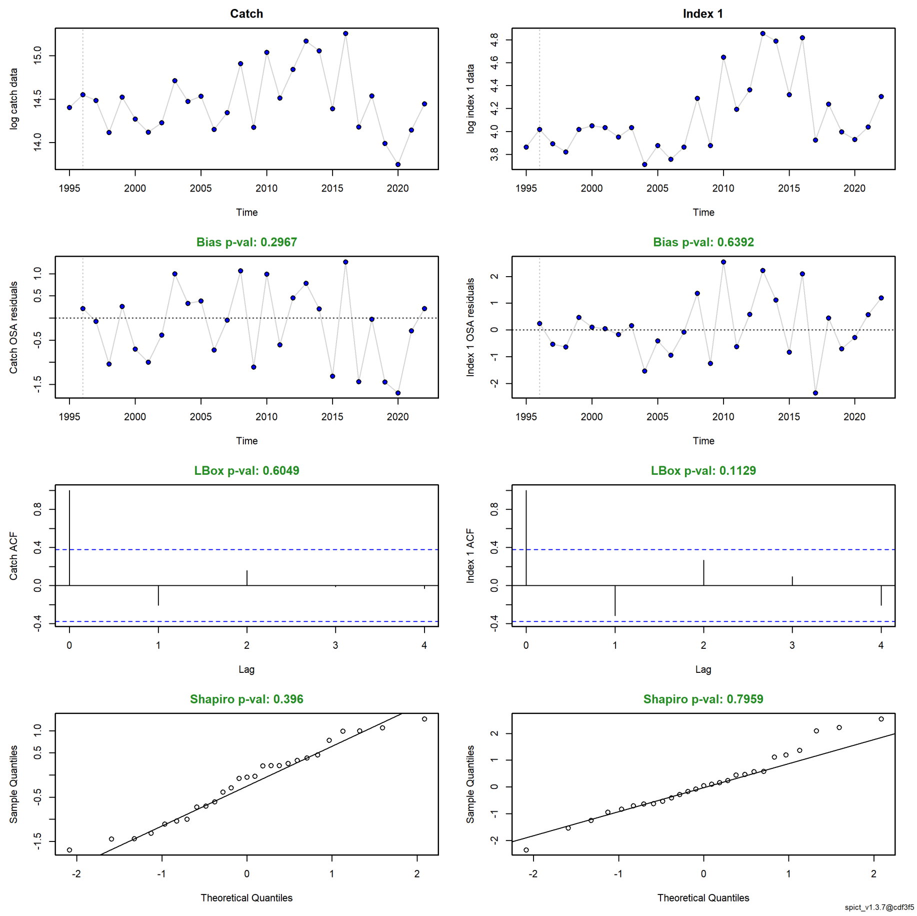


FIGURE 4.17: Diagnostic plots for the SPiCT model fit of the octopus fishery from the polyvalent fleet in the Portuguese Western Coast between 1995 and 2022, aggregated by year.

With data regarding the octopus fishery from the polyvalent fleet in the Southern region of Portugal, the *SPiCT* model fit yielded more grounded results, albeit with large uncertainty associated with them (Table 4.9). The estimates for K and MSY were 4740 tons and 2043 tons/year, results that are more in line with both *CMSY++* and *JABBA*. Stock biomass is estimated to have been below B_{MSY} levels at the beginning of the series and has experienced accentuated oscillations since, occasionally dipping below the recommended levels.

Fishing mortality, on the other hand, while above recommended levels at the start of the series, is estimated to be on a downward trend, stabilizing below F_{MSY}. As a result, the stock is presented as being on a good trajectory (Figure 4.18).

TABLE 4.9: Parameter estimates from the SPiCT model fit to the octopus landings from the polyvalent fleet in the Southern region of Portugal in terms of estimates (estimate and log.est), lower confidence interval (cilow) and upper confidence interval (ciupp).

parameter	estimate	cilow	ciupp	log.est
alpha	0.05	0.00	71.04	-3.08
beta	2.70	0.74	9.92	0.99
r	1.93	0.71	5.25	0.66
rc	1.93	0.71	5.25	0.66
rold	1.93	0.71	5.25	0.66
m	2281788.94	1699101.77	3064301.88	14.64
K	4740823.83	1438667.97	15622375.00	15.37
q	0.00	0.00	0.00	-10.48
sdb	0.32	0.22	0.47	-1.13
sdf	0.08	0.03	0.27	-2.48
sdi	0.01	0.00	21.92	-4.20
sdc	0.23	0.16	0.32	-1.48
Bmsys	2130972.30	564025.52	8051130.23	14.57
Fmsys	0.96	0.32	2.87	-0.04
MSYs	2042684.01	1507351.05	2768139.49	14.53

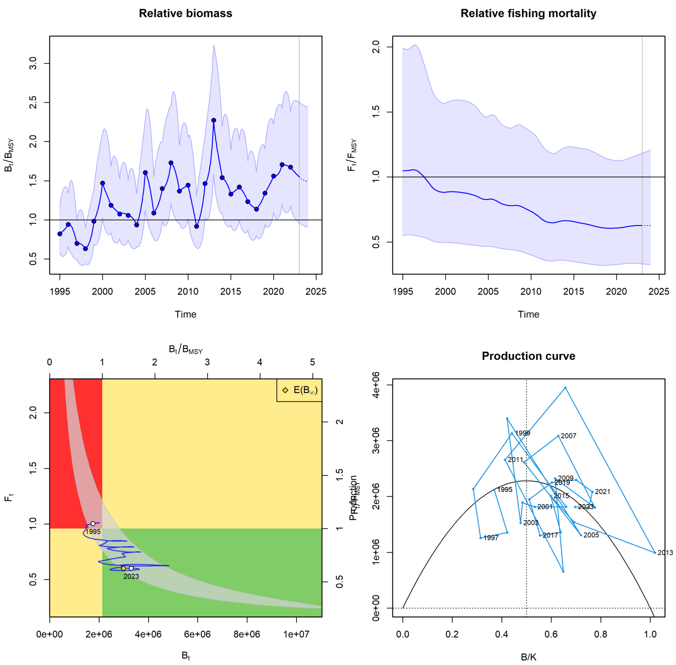


FIGURE 4.18: Results from SPiCT model fit to the octopus fishery from the polyvalent fleet in the Portuguese Southern Coast between 1995 and 2022, aggregated by year: estimated biomass over BMSY (top left), estimated fishing mortality over FMSY (top right), Kobe plot with the fishing mortality vs biomass trajectory (bottom left) and surplus production curve with trajectory (bottom right).

As with the fit for the Western region, the retrospective analysis showed the model is consistent and resilient to loss of recent data, despite the unreasonably large confidence intervals (Figure 4.19). Both ρ statistics for B/B_{MSY} and F/F_{MSY} fall between the range of -0.15 and 0.22. Model residuals presented no evidence for serial autocorrelation under Ljung-Box test (Figure 4.20).

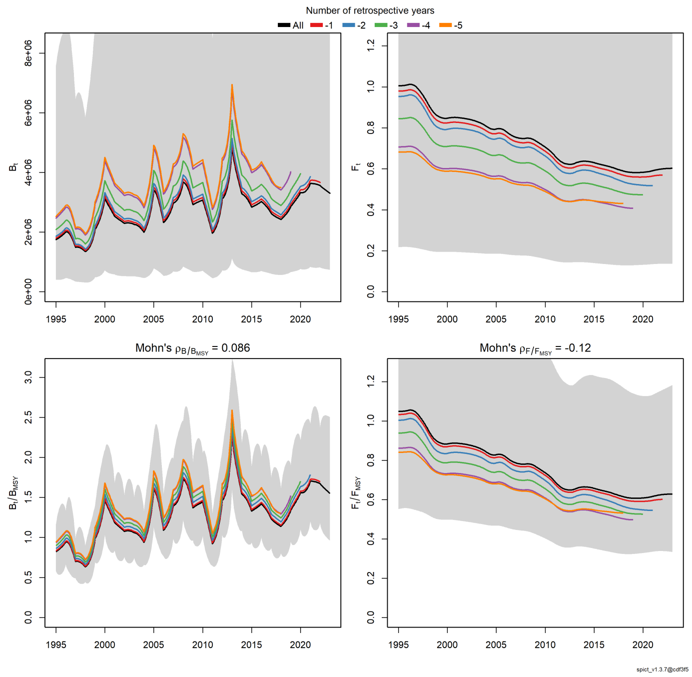


FIGURE 4.19: Retroactive plots for the SPiCT model fit of the octopus fishery from the polyvalent fleet in the Portuguese Southern Coast between 1995 and 2022, aggregated by year.

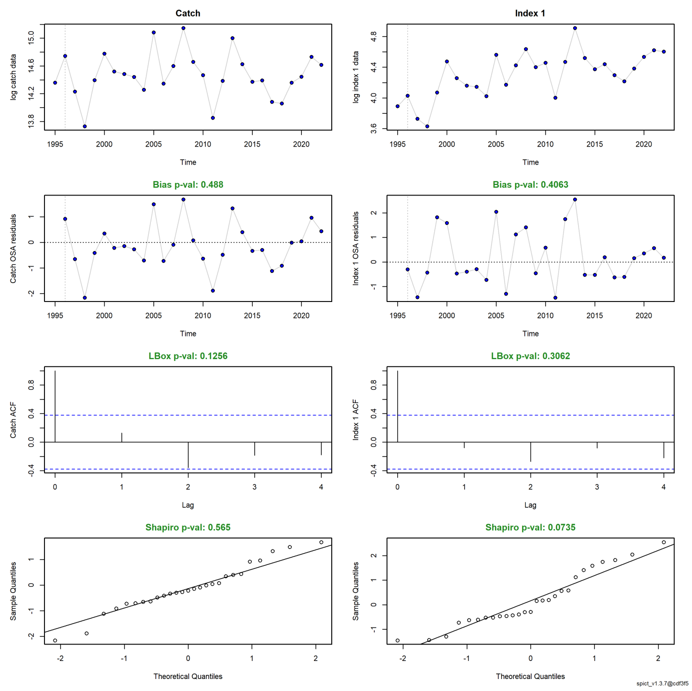


FIGURE 4.20: Diagnostic plots for the SPiCT model fit of the octopus fishery from the polyvalent fleet in the Portuguese Southern Coast between 1995 and 2022, aggregated by year.

4.4.2 Method evaluation

From a developing standpoint, *SPiCT* is easily the most mature framework out of those tested in this work. The documentation is extensive, both from a scientific and a technical standpoint. Input formatting is simple enough, requiring only the assignment of the series to a list with predefined names. Priors and hyperparameters are then stored as objects in that list. The model results are stored in a custom class. The fitting procedure also stores computing time of the fitting process on the object. Plots are in base *R* and each plot can be either created individually or in some sets of predefined panels.

While *SPiCT* has some challenging dependencies on first installation, once a stable *R* environment has been created it can be deployed easily in a service like *ShinyApps*. *SPiCT*'s largest drawback lies in the performance. Table 4.10 presents the times for the sucessful convergences, which are in line with previous results from the other frameworks. However, failure to converge immediately, specially in models with more granular time steps that, unlike the other frameworks, SPiCT can accommodate, often results in running times of several hours on a local machine. Despite being able to sucessfully implement the models presented this work in a *ShinyApp* flex-dashboard published on *Shinyapps.io*, the app becomes borderline unusable once a SPiCT fit is attempted.

TABLE 4.10: Run times for *SPiCT* fitting by framework (different source data) and time spend (seconds) in each process phase (pre-process, modelling fit and render of outputs).

Framework	Phase	Time
SPiCT - Polyvalent, Western Coast, Yearly data	Pre.process	0.23
SPiCT - Polyvalent, Southern Coast, Yearly data	Pre.process	0.33
SPiCT - Polyvalent, Western Coast, Yearly data	Model.fit	18.23
SPiCT - Polyvalent, Southern Coast, Yearly data	Model.fit	19.37
SPiCT - Polyvalent, Western Coast, Yearly data	Output.Render	1.79
SPiCT - Polyvalent, Southern Coast, Yearly data	Output.Render	1.57

4.5 CatDyn

4.5.1 Octopus stock assessment

In order to assess the presence of catch spikes in the Western region landings of the polyvalent fleet in 2022, *CatDyn*'s built-in diagnostic plots were used (Figure 4.21). In this series, the most prominent catch spike occurred at week 43, though it was not accompanied by a decrease in mean body weight that would signal an influx of recruits in the fishery. For lack of clearer alternatives, a single scenario of 1 perturbation at week 43 was tested.

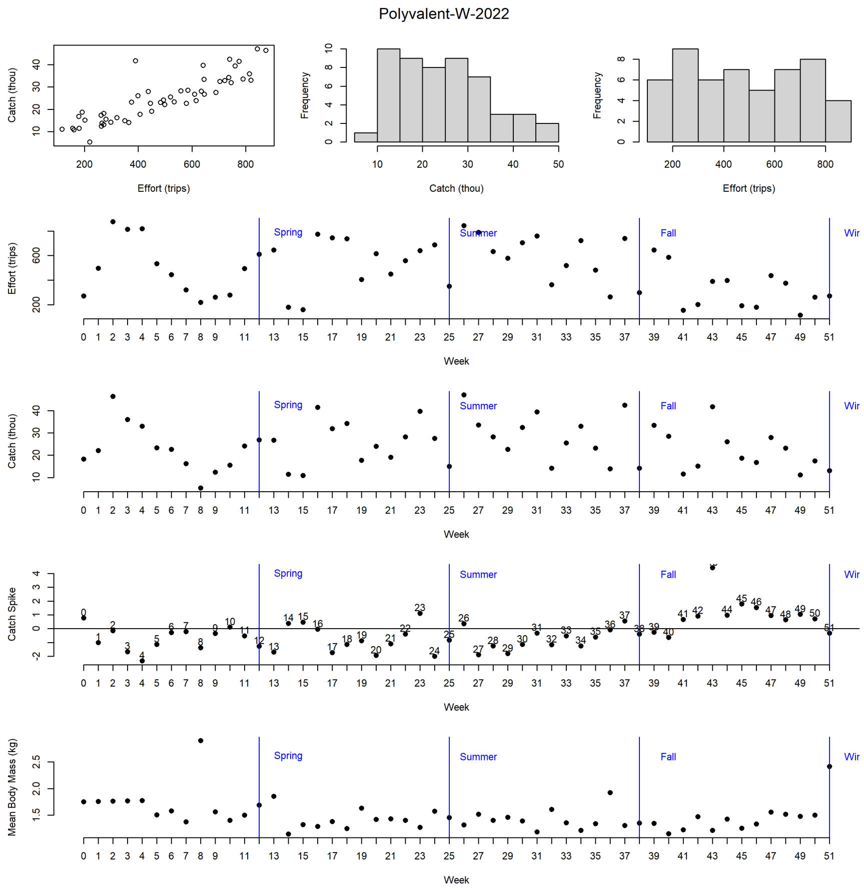


FIGURE 4.21: Diagnostic plots for the weekly octopus landings from the polyvalent fleet in the Western region of Portugal in 2022. From top to bottom: catch vs effort scatterplot, catch and effort histograms (thousand individuals), effort time series in number (thousand individuals), catch series in number (thousand individuals), catch spike series (adimensional) and mean body weight series (kg).

In the Western Region, 16 models were fit with all possible combinations of the 4 distributions and 4 optimizers considered. The combinations of normal distribution with Nelder-Mead optimizer and lognormal distribution with BFGS optimizer failed to converge and were therefore rejected. The remaining models (Table 4.11) all failed to estimate plausible natural mortality rates, with all estimates M being lower than 0.002. 4 of the models failed to provide standard deviation for some estimates, which indicates convergence problems.

TABLE 4.11: Summary of the hyperparameters and results of each model fit with *CatDyn* to weekly landings data of the octopus fishery by the polyvalent fleet in the Western region of Portugal in 2022. AIC = Akaike Information Criterion, M.A.G. = Maximum Absolute Gradients, M = natural mortality rate, N0 = population at the beginning of the season, P1 = amplitude of catch spike P1 (in number of individuals), ts.P1 = time step of catch spike P1, k = scaling factor of the catch function, alpha and beta = power modulator of catch and abundance index. Standard deviation of the estimates are denoted by the prefix *'SE.'*.

Distribution	Method	AIC	M.A.G.	M	SE.M	N0	SE.N0	P1	SE.P1	ts.P1	k	SE.k	alpha	SE.alpha	beta	SE.beta
negbin	CG	308.88	0.03	0.00	0.00	54063.91	444450.80	332255.04	3566384.17	43.00	0.01	0.19	0.89	0.07	0.19	1.27
negbin	spg	309.00	0.83	0.00	0.00	30568.47	117657.24	152379.59	715219.47	43.00	0.01	0.04	0.89	0.07	0.21	0.33
negbin	BFGS	308.77	0.11	0.00	0.00	1200119.03	27492981.77	6135058.43	164152546.16	43.00	0.01	-	0.89	0.07	0.21	-
negbin	Nelder-Mead	308.93	1.04	0.00	0.00	70105.69	255485.38	62934.45	249530.00	43.00	0.00	0.00	0.89	0.07	0.59	0.57
normal	CG	310.09	0.11	0.00	-	21762.47	-	144297.83	-	43.00	0.01	-	0.96	0.08	0.20	-
normal	spg	309.88	0.30	0.00	0.00	51592.34	243028.19	403339.75	2468007.53	43.00	0.01	0.05	0.96	0.08	0.19	0.46
normal	BFGS	309.75	0.24	0.00	0.00	1601041.58	45836431.58	6759699.50	214444267.73	43.00	0.00	0.01	0.96	0.08	0.25	0.57
lognormal	CG	316.38	0.01	0.00	0.00	587386.28	11282117.92	7525737.20	175942124.85	43.00	0.02	0.25	0.85	0.06	0.14	0.88
lognormal	spg	316.43	0.02	0.00	0.00	103837.21	1237118.59	637758.74	9677600.54	43.00	0.02	0.36	0.85	0.06	0.18	1.87
lognormal	Nelder-Mead	316.38	0.51	0.00	0.00	993156.01	38854084.94	402312142.79	19935242909.14	43.00	0.05	0.16	0.85	0.06	0.06	0.20
gamma	CG	-222.32	0.00	0.00	0.01	122855.98	6658152.66	737673.57	50202179.25	43.00	0.02	1.74	0.83	0.23	0.18	8.39
gamma	spg	-222.27	0.03	0.00	-	11869.43	-	32295.06	-	43.00	0.01	-	0.83	0.23	0.26	-
gamma	BFGS	-222.32	0.08	0.00	0.01	189233.98	6401771.05	1527129.79	63862425.32	43.00	0.02	-	0.83	0.23	0.16	-
gamma	Nelder-Mead	-222.28	0.44	0.00	0.04	8100.40	68768.02	269272.41	4985766.97	43.00	0.07	0.34	0.81	0.23	0.09	0.49

Based on the correlation between parameter estimates (Figure 4.22), Model 4 (negative-bionmial with Nelder-Mead optimizer) would be the best fit since correlations are closer to 0, but with a maximum numerical gradient above 1, it is more prudent to also exclude this model [32]. Therefore, Model 3 (negative binomial with BGFS optimizer) was chosen.

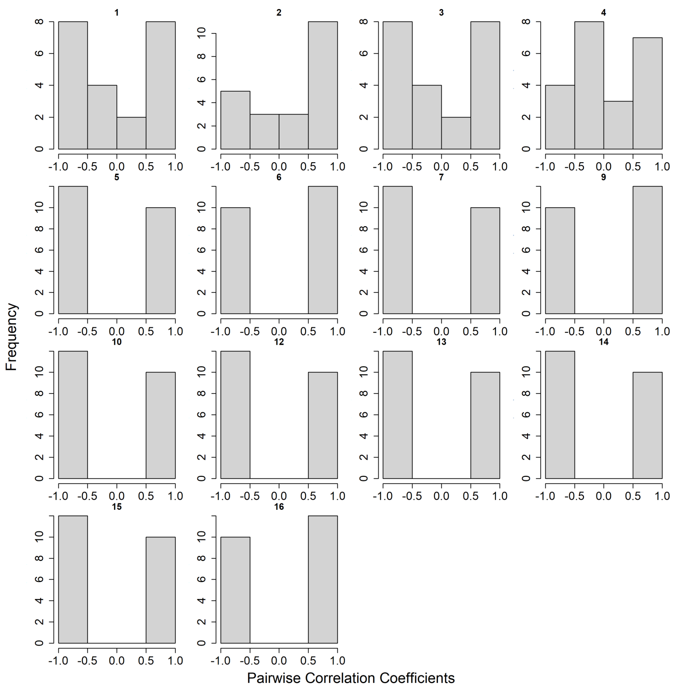


FIGURE 4.22: Parameter estimates correlation for all 14 models (models 8 e 11 were excluded) fit to the weekly landings data from the polyvalent fleet in the Western region of Portugal in 2022.

For the Western Region, the predicted catch by Model 3 is presented in Figure 4.23. Although the fit between predicted and observed catch and the deviance of residuals appears reasonable at first glance, concerns about the estimates for *M* and high correlation between many of the parameter estimates should be kept in mind.

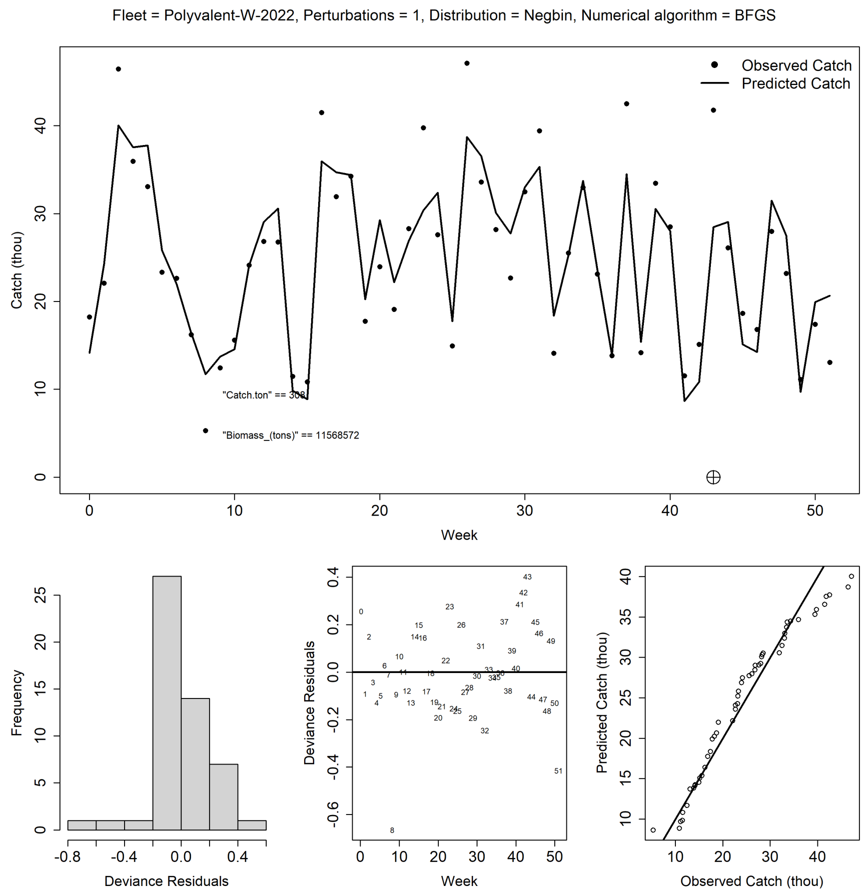


FIGURE 4.23: Predicted and observed catch plots, with residual dispersion plots from the Model 3 fit to the weekly landings data from the polyvalent fleet in the Western region of Portugal in 2022.

In the Southern region, a single plausible catch spike was observed at week 2 (Figure 4.24), which was the only scenario considered for this analysis. Like before, it was not accompanied by a a dip in mean body weight and the spike in mean body weight at week 3 is likely to be an outlier in the sampling.

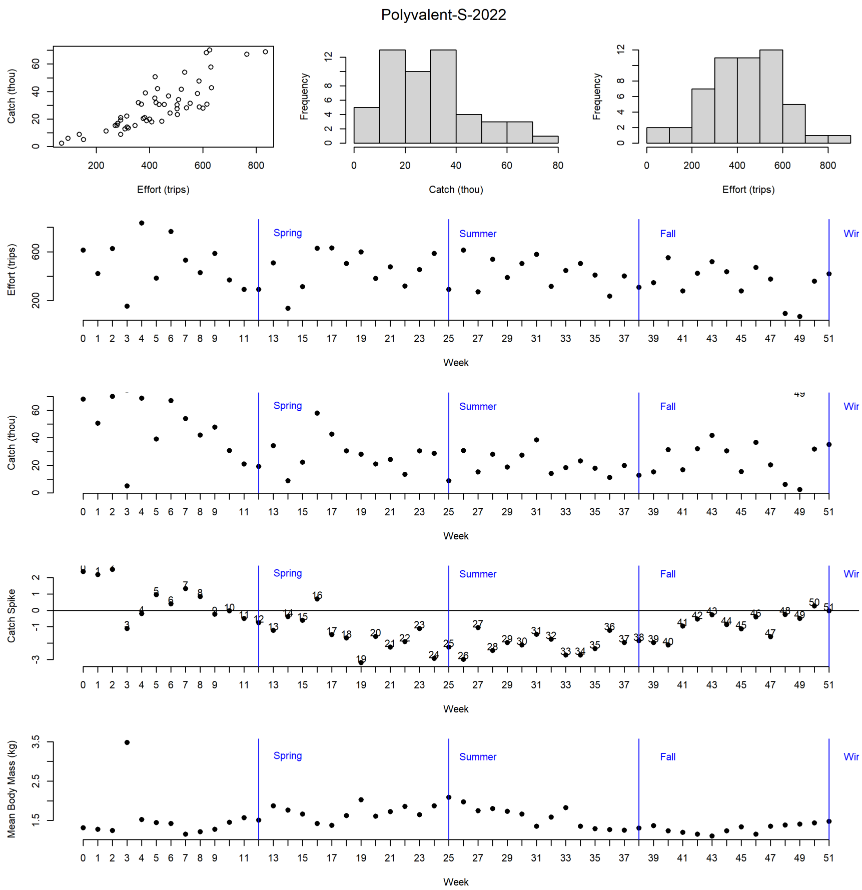


FIGURE 4.24: Diagnostic plots for the weekly octopus landings from the polyvalent fleet in the Southern region of Portugal in 2022. From top to bottom: catch vs effort scatterplot, catch and effort histograms (thousand individuals), effort time series in number (thousand individuals), catch series in number (thousand individuals), catch spike series (adimensional) and mean body weight series (kg).

Of the 16 models that were fit under the 1 perturbation scenario at week 2, 5 failed to provide dispersion estimates for all parameters and none estimated a plausible value for *M* (Table 4.12). No model was excluded under the criterion of maximum absolute gradient. However, all models presented very high correlation between parameter estimates (Figure 4.25).

TABLE 4.12: Summary of the hyperparameters and results of each model fit with *CatDyn* to weekly landings data of the octopus fishery by the polyvalent fleet in the Southern region of Portugal in 2022. AIC = Akaike Information Criterion, M.A.G. = Maximum Absolute Gradients, M = natural mortality rate, N0 = population at the beginning of the season, P1 = amplitude of catch spike P1 (in number of individuals), ts.P1 = time step of catch spike P1, k = scaling factor of the catch function, alpha and beta = power modulator of catch and abundance index. Standard deviation of the estimates are denoted by the prefix *'SE.'*.

Distribution	Method	AIC	M.A.G.	M	SE.M	N0	SE.N0	P1	SE.P1	ts.P1	k	SE.k	alpha	SE.alpha	beta	SE.beta
negbin	CG	361.79	0.01	0.03	-	6814672.61	-	173.52	-	2.00	0.00	-	1.20	0.11	0.26	-
negbin	spg	361.80	0.01	0.03	0.63	892838.29	44342799.35	279.64	20387.90	2.00	0.00	0.04	1.20	0.11	0.26	5.17
negbin	BFGS	361.79	0.00	0.02	-	434608026.56	-	134.52	97471.44	2.00	0.00	0.00	1.20	0.11	0.35	-
negbin	Nelder-Mead	361.79	0.07	0.09	0.85	33062885.62	1462410013.11	5.01	10372.67	2.00	0.01	0.06	1.20	0.11	0.09	0.80
normal	CG	372.32	0.07	0.05	0.15	204233.73	1689963.23	444.12	6102.19	2.00	0.00	0.02	1.04	0.12	0.31	0.98
normal	spg	372.19	0.01	0.04	0.18	1354944.50	19340712.52	302.10	9325.06	2.00	0.00	0.01	1.04	0.12	0.32	1.29
normal	BFGS	372.17	0.15	0.04	0.10	18334193.31	601601451.97	120.99	18604.89	2.00	0.00	0.01	1.04	0.12	0.33	0.74
normal	Nelder-Mead	372.17	0.37	0.03	0.03	60827599.02	980447904.37	840.42	77421.69	2.00	0.00	0.00	1.04	0.12	0.44	0.44
lognormal	CG	361.73	0.01	0.03	-	365340.59	-	305.28	-	2.00	0.00	-	1.21	0.09	0.23	-
lognormal	spg	361.73	0.32	0.03	0.12	526308.13	14969830.83	276.42	11489.59	2.00	0.00	0.01	1.21	0.09	0.24	1.07
lognormal	BFGS	359.23	0.11	0.00	0.00	9376.61	12234.50	0.23	9.94	2.00	0.00	0.00	1.20	0.08	2.37	3.54
lognormal	Nelder-Mead	361.73	0.13	0.04	0.27	713638.00	16173420.80	10.39	1925.74	2.00	0.00	0.03	1.21	0.09	0.18	1.36
gamma	CG	-210.67	0.00	0.03	-	293217.31	-	312.89	-	2.00	0.00	-	1.19	0.25	0.23	-
gamma	spg	-210.66	0.04	0.03	0.50	59729.31	2239853.21	531.79	28736.73	2.00	0.00	0.07	1.19	0.25	0.21	3.01
gamma	BFGS	-210.67	0.07	0.02	-	648268.99	-	542.98	-	2.00	0.00	0.01	1.19	0.25	0.31	-
gamma	Nelder-Mead	-210.60	0.25	0.08	0.46	759942.08	22865564.64	204898.28	7146661.67	2.00	0.01	0.04	1.18	0.25	0.08	0.42

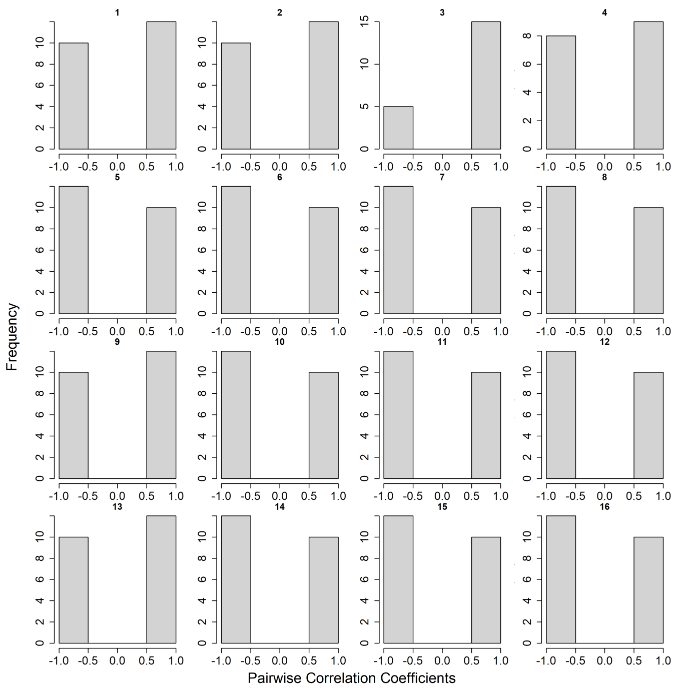


FIGURE 4.25: Parameter estimates correlation for all 16 models fit to the weekly landings data from the polyvalent fleet in the Southern region of Portugal in 2022.

Under these circumstances, it is not reasonable to select a better fit and further analysis would be required to reattempt the fitting process. As an illustration, results for Model 4 are presented in Figure 4.26.

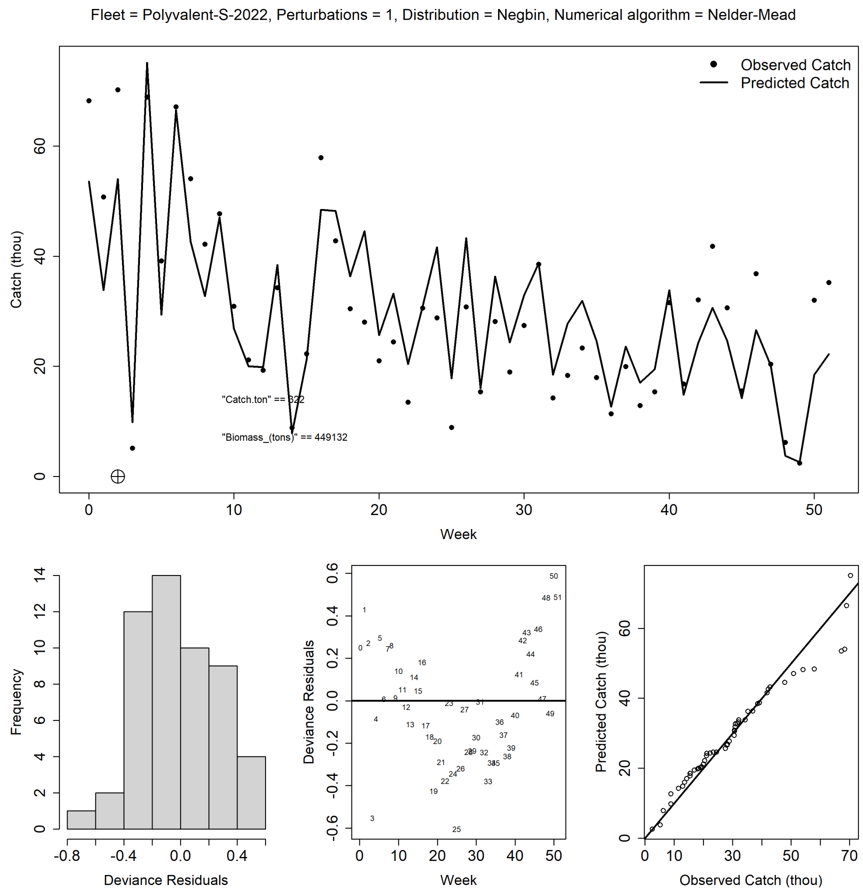


FIGURE 4.26: Predicted and observed catch plots, with residual dispersion plots from the Model 4 fit to the weekly landings data from the polyvalent fleet in the Southern region of Portugal in 2022.

4.5.2 Method evaluation

Performance times were not measured for *CatDyn* due to the amount of manual iterations and oversight required from the user. On a local machine, each fit attempt lasted from several seconds to under a minute. Integration into the *Shiny* app was possible without any significant obstacle, based on the built-in functions and plotting methods.

4.6 Results from the bottom trawl fleet

The analysis presented focused on the dataset pertaining to the landings from the polyvalent fleet, as this is fleet accounts for over 90% of total landings and is understood to actively target octopus. An abbreviated form of the analysis was also conducted on the data from the bottom trawl fleet and their results are included in Appendix C. *CatDyn* was not applied to this data as biological data regarding sex ratios and mean weight estimates for this fishery were not available at the time of this study. A similar trend to the polyvalent results was observed where results from *CMSY++* as a whole were more conservative than those from *JABBA* and *SPiCT*. Noticeably, no estimates for *MSY* were produced for the Southern region dataset, indicating a problematic model fit. Other than assessing whether the methods could successfully converge on the dataset, no further analysis was conducted at this time.

4.7 Summary

A quick overview of the different fits is presented in Tables 4.13 and 4.14, where the estimates for some biological reference points for common octopus can be compared for each fit.

TABLE 4.13: Parameter estimates from each framework after fitting variations from several surplus production models to the Portuguese polyvalent fishing data on octopus in the Western region of Portugal. Parameters labeled with *(a)* refer to estimates for the final year in the series (2022).

Model Parameter	units	CMSY++ CMSY	CMSY++ BSM	JABBA Schaefer	JABBA Pella	JABBA Fox	SPiCT -
q	adim.	-	0.426	≈ 0	≈ 0	≈ 0	≈ 0
mp	adim.	-	-	2.00	1.19	1.00	-
r	adim.	0.76	0.608	0.24	0.23	0.23	0.29
K	1000 tons	13	14.6	70.3	61.9	53.4	120.1
MSY	1000 tons	2.46	2.23	4.05	4.84	4.48	7.57
F_{MSY}	adim.	-	0.304	0.12	0.19	0.23	0.14
B_{MSY}	1000 tons	-	7.32	35.16	24.79	19.66	55.7
B/B_{MSY} (a)	adim	-	6.46	1.76	2.16	2.79	-
B/K (a)	adim.	0.337	0.337	*	*	*	-
F (a)	adim.	-	0.338	*	*	*	-
F/F_{MSY} (a)	adim.	-	1.11	0.26	0.18	0.18	-
$F/r/2$ (a)	adim.	1.01	1.25	*	*	*	-

Estimates for the Western coast (Table 4.13) are consistently higher than those of the Southern Coast of Portugal (Table 4.14). *JABBA* estimates for q are not explicitly reported, but are can be accessed in the object resulting from the model fit. Estimates marked with $*$ are not explicitly reported, but can be calculated with the provided estimates.

Performance of all methods is presented in Figure 4.27. As it was previously mentioned, *CatDyn*'s performance times were not recorded due to the ammount of manual intervention necessary. Aside from the discrepancy between the performance of *CMSY++*'s

TABLE 4.14: Parameter estimates from each framework after fitting variations from several surplus production models to the Portuguese polyvalent fishing data on octopus in the Southern region of Portugal. Parameters labeled with *(a)* refer to estimates for the final year in the series (2022).

Model Parameter	units	CMSY++ CMSY	CMSY++ BSM	JABBA Schaefer	JABBA Pella	JABBA Fox	SPiCT -
q	adim.	-	0.468	≈ 0	≈ 0	≈ 0	≈ 0
mp	adim.	-	-	2.00	1.19	1.00	*
r	adim.	0.76	0.710	0.31	0.45	0.37	1.93
K	1000 tons	11.8	12	46.3	17.9	22.3	4.7
MSY	1000 tons	2.23	2.14	3.46	2.54	2.99	2.04
F_{MSY}	adim.	-	0.355	0.15	0.38	0.37	0.96
B_{MSY}	1000 tons	-	6.01	23.2	71.8	81.8	2.1
B/B_{MSY} (a)	adim	-	0.612	1.95	2.10	2.54	*
B/K (a)	adim.	0.404	0.404	*	*	*	*
F (a)	adim.	-	0.62	*	*	*	*
F/F_{MSY} (a)	adim.	-	1.74	0.35	0.42	0.29	*
$F/r/2$ (a)	adim.	1.22	1.29	*	*	*	-

pre-processing stage in the Western and Southern region datasets, all methods were internally consistent, with slighter faster performance with the Southern dataset at all stages of the process. Overall, *JABBA* presented the faster performance, with *SPiCT* closely behind. *CMSY++* performed significantly slower at all stages.

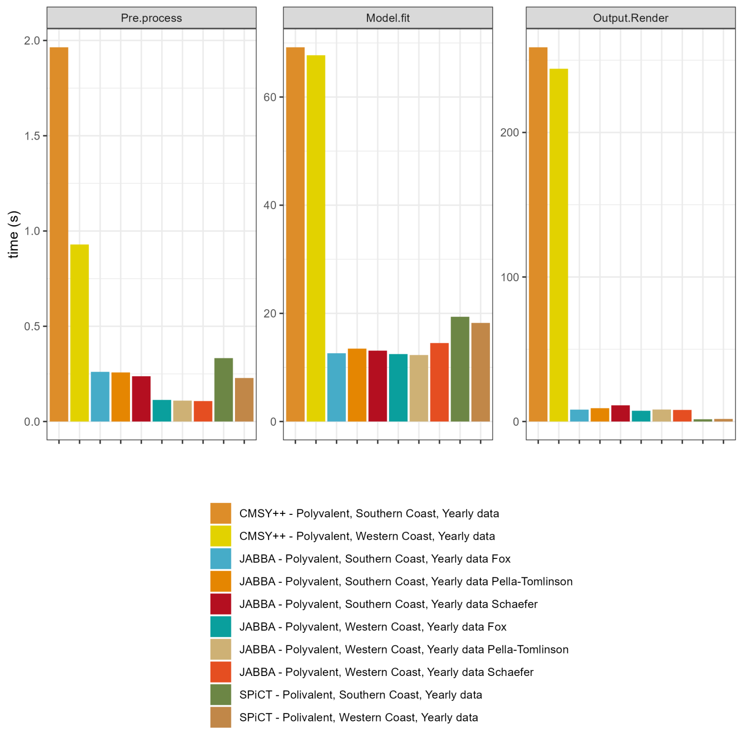


FIGURE 4.27: Performance times, in seconds, of each framework at each stage of fitting a surplus production model to the Portuguese polyvalent fishing data on octopus in the Western and Southern regions of Portugal.

In the next section, these results are discussed in regard to the applicability of the estimates for stock assessment, the implications of the discrepancies observed and the obstacles that were met in the goal of providing a tool for divulging stock assessment results.

Chapter 5

Discussion

Octopus stock assessment overview

The landings from the polyvalent fleet in both the Western and Southern regions of Portugal have experienced growth for in the last 2 years for the first time since their crash from historical highs in 2017.

There appears to be a cyclical behaviour in the yearly landings which lends some strength to the equilibrium assumption that *SPM* hold, with the bigger changes being in variance of the series. The analysis performed was less conclusive on the strength of a seasonal effect, with seasonal differentiation not being strictly a requirement to make the series stationary (Table 4.1). However, the evidence towards the fisheries operating in a deliberately seasonal fashion in their decision to actively target octopus [45] should not be ignored. The ability to include seasonality and intra-anual variability should be a factor to consider when choosing a stock assessment method.

The application of different methods to the Portuguese octopus landings datasets resulted in very different assessments, ranging from overfishing (*CMSY++*) to flourishing and barely exploited (*SPiCT*). All frameworks were consistent in two points: the Western stock is larger than the Southern stock, and their estimates for *MSY* ranges between 2000 and 7500 tons for each stock. While these figures are contingent on the accuracy of the model fits, the fact that the range of estimates is close to, and often under, the reported year landings is concerning. Current assessment of octopus stocks by *ICES* reports a decreasing tendency for the 3-year period of 2019-2021, with the average annual landings for Western Iberia and Gulf of Cadiz in this period being 7534 tons/year, below the historical mean of 11533 tons/year [22]. It would seem that at this point, there is cause for moderate concern on the status of the fishery in both regions and the variability of the estimates obtained on this work is too high to support a conclusion on the status of the stock, given that shifts in the order of hundreds of tons of the *MSY* can result in changes from safe assessment to overfishing estimation.

The application of *CMSY++* resulted in fairly conservative estimates for stock size and *MSY*. This method is restricted to annual data and a Schaefer production curve, which raise some questions towards its suitability for a fishery like octopus [73]. The assumption of equilibrium in the stock can not be taken for granted, and restricting that assumption to a symmetrical shape, with peak surplus production being achieved at exactly half of the carrying capacity is, without aditional evidence, arbitrary at best. Still, as a baseline scenario, *CMSY++* fit the data remarkably well, with the tighter confidence intervals for its estimates.

Results from *JABBA* models were less conservative than those obtained with *CMSY++*. While there are significant differences between each model formulation, even the estimates obtained with Schaefer's formulation are markedly different than *CMSY++*'s implementation. Carrying capacity is estimated to be 4 or 5 times higher in *JABBA*. While model formulation choice obviously plays a role in the outcome, it does not appear to be the driving factor behind the differences in the estimates. For the Western region, *MSY* estimates range from 4050 to 4840 tons, almost the double of *CMSY++*' estimate of 2230 to 2460 tons. Other than default priors that, in good conditions, should have converged to similar estimations given the same input data, the biggest difference between these methods is *JABBA*'s capability of explicitly incorporating abundance index dispersion data through user-specified input. While this capability does in theory lead to a more robust estimation, it will also propagate any problems in the data collection and standardization that may exist.

SPiCT would be, in theory, the best suited method for the task. The capability of working with sub-annual data and in continuous time, allowing for gaps in abundance data would appear to be a good match for a fast-growing species with limited data on effort. *SPiCT* is in fact an accepted stock assessment method for *ICES* [6, 70], which would make it in theory a good candidate for a formal assessment of octopus stocks. Previous trials with *SPiCT* fit to fishery data of the Southern region led to inconclusive results regarding the quality of the estimates obtained through this method [71]. The results obtained in the present work follow a similar pattern. The *MSY* estimates are somewhat in line with those obtained with other methods, despite the estimate for the Western region (7570 tons) being the highest by a large margin. The 2040 tons estimate for the *MSY* in the Southern region is the lowest estimate for the region, albeit by a small difference from the 2140 tons obtained with *CMSY++*. The remainder estimates, however, portray a completely different stock dynamic, with carrying capacities orders of magnitude higher than those estimated by other methods. Growth coefficient estimates for octopus obtained with *SPiCT* for the Western region is in line with the estimate from *JABBA*, but the estimate of 1.93 obtained for the Southern region is unreasonably high (Table 4.14).

The preliminary results obtained from the different methods show that while they are, on a surface level, compatible with the data available for the octopus fisheries in Portugal. More importantly, it provided an example of how volatile the outcome of the analysis may be if all required considerations at the input stage are not given. *CMSY++* implementation of the catch only method was capable of providing a plausible stock scenario. While *JABBA* and *SPiCT* allowed for a more statistically robust framework by incorporating index and process error in a more explicit manner, in this particular example the result had a much wider confidence range as a consequence.

In the *SPiCT* trials, the symmetry parameter was set to Schaefer's production curve. This choice was meant to provide a common ground between all 3 *SPM* methods. The fact that stock status estimates were so disparate appears to indicate that production curve shape, while relevant, may not be the determining factor in the quality or consistency of the assessments. In other comparisons of stock assessment frameworks based on *SPM* [6, 109], the importance of good estimates for prior information on stock status to be passed to the model is well stated. Estimates on r, initial relative biomass B_0/K or the biomass threshold at which r is compromised may have significant impact in the stock assessment. In the future, if a *SPM* method is to be used, then a careful sensitivity analysis should be carried on all relevant priors.

It is uncertain, however, whether a *SPM* will be the most appropriate choice for the Portuguese octopus fishery. Some authors have called into question the pertinence of the concepts of equilibrium as it applies to cephalopods and the usefulness of *MSY* as a management tool for them [32, 73]. In that context, *CatDyn*'s emphasis on intra-annual dynamics and a reconstructed, modelled catch as opposed to nominal catches appear as a very viable alternative. Unfortunately, it was not possible to completely apply this methodology in this work.

None of the models that were fit can be considered adequate to proceed into the second stage of the framework assessment. While there was a pattern of the negative binomial distribution being the best approximation out of the models attempted, this distribution was only included in the test for it successful convergence in the preliminary tests. The package author states in the documentation that it is meant to be used with count data as an alternative to the Poisson distribution [80], so the plausibility of such estimates should be met with some scepticism. Still, with preliminary knowledge of the methodology, it stands to reason that it should be heavily considered in the continuation in this work.

In order to improve the reliability of the stock assessment for the Portuguese octopus fishery, additional work is required at the input stage of the model stage. There are two main points of contention regarding data quality that could not be addressed in the scope of this work and that can not be ignored.

The first point is the need of an estimation, even if preliminary, of the proportion of *Eledone spp.* that has been aggregated in the reported landings in the earlier part of the series. Separate reported landings *Eledone spp.* from octopus exist since 2009 [22], and despite some reservations towards the accuracy of the reservation (considering the aggregate designation *'OCT'* remained in use until 2016), total reported landings for *Eledone spp.* in Portuguese waters never exceeded 150 tons/year [22]. While accurate estimation of the true octopus proportion in the early years of the series is worth pursuing, this factor would not seem to be the main source of uncertainty in assessing the status of the fishery.

The other main issue is the potential need for the standardization of the abundance index. While the practice itself has become standardized [48], it is, in theory, not mandatory, should the catchability constance and catch-abundance dependence assumptions hold. In fact, works based on *GDM* implementation do not explicitly standardize the effort through modelling [32], though the choice of number of vessels as an effort indicator accounts for this. However, in the Portuguese octopus fishery data there is enough evidence to assume that 1) the series is long enough and the fishery heterogenous enough that a constant q is not expectable and 2) there is lack of contrast in the series. Lack of contrast occurs when there is not enough variation in the response between effort and catches, i.e. they are too positively correlated. This is a known obstacle in *SPM* and can be addressed through standardization [6]. The failure in applying a known standardization method to the *LPUE* series in this work may have compromised the quality of the estimates obtained.

In a future work, this limitation must be adressed. An alternative approach for effort indexes standardization that is directed towards the specificities of octopus small-scale fisheries has been developed by Lourenço and Pereira [94]. The proposed approach derives a standardized abundance index by only accounting for the second of 2 consecutive day landings from each vessel, which ensures that the effort per trip can never exceed one day. This approach was not used in this work since a preliminary attempt at designing an algorithm that would restrict the dataset to the desired trips raised several practical problems. While solving them would have exceeded the time frame available for this work, results from the original paper [94] are promising enough to warrant revisiting this approach in a formal assessment of the Portuguese octopus stock.

Ultimately, all methods were successfully tested in the scenario of the octopus fishery in Portugal. A reiteration of the work performed here should prioritize on achieving a refined catch series that excludes incorrectly aggregated data, an abundance index standardized through the approach presented in [94], modelling the catch dynamic through *CatDyn* and using the fitted series either with one of the considered models or altogether another stock assessment approach.

Methods overview

CMSY++ presented arguably the most laborious input stage. While the documentation is quite thorough on the format specifications, the format itself is by no means universal. Considerable time and effort is expected from the user to either convert their data into a compatible **.csv* file with the data structure required or to pipeline their data in the script itself. On a single stock this is a trivial task, but exercises aiming to assess multiple stocks by pooling data from different sources will spend considerable more time on the input stage, compared to the other methods. The plots are created in base R and can be set to be recorded in the source directory. Most plots are aggregated on panels, by default, though the individual elements are left accessible in the environment after each run, at which point they can be accessed and manipulated. The optional report is also compiled through *LATEX* is a very valuable functionality, providing a quick distributable summary at a glance. Its generation is by default encapsulated in a *for()* loop, so edition or interaction of each individual element is impossible without heavily alterations to the original script.

CMSY++ was by far the hardest method to incorporate into the *Shiny* app. The entire script had to be refactored and broken out of the conditional *if... else* structures in order to be used in a reactive environment, which led to plenty opportunities for introducing bugs and user error. The performance issues were amplified on the deployment to *shinyapps.io*.

From an implementation standpoint, both *JABBA* and *SPiCT*, proved to be more accessible, with the built-in functions and custom classes proving to be both easy to use and to transition to the *Shiny* app. The performance times were on par, with *JABBA* being faster in the pre-processing and fitting stages and *SPiCT* faster on the output rendering stage. Both methods were significantly faster than *CMSY++*, even before accounting for lag introduced in the *IDE*.

CatDyn inclusion in the app served only the purpose of illustration. While the package is well suited for integration into an app, the method itself is not. It requires user intervention at every step, with the manual selection of catch spike combinations. The decision on whether to include exit pulses in the model and the choice of approach for the second stage of the hierarchical framework also require close analysis at every step. All these steps could in theory be automated, but doing so weaken one of the advantages of this method, which is a more informed and well-fitted description of the catch dynamic. While the same could be said about the *SPM* methods considered, *CatDyn* really brings to the forefront the fact that just because some steps can be automated, it may be wise not to attempt to do so.

An issue that became evident through the parallel implementation of these methods was the differences found in conventions and notation. For example, the expectation on whether some input parameters should be logarithms by the user differs in *JABBA* and *SPiCT*. The notation regarding the formulation for the production curve is also implement differently in each method. In *JABBA*, the user is guided to the corresponding flag and forced to make a decision on whether to interact with it or leave it on the default (Schaefer). In *SPiCT*, however, that settings isn't controlled by a numerical attribute of the production curve, that can be left at default, meaning the user may not ever need to interact with it. If the user were to parse the documentation, *prior$n=log(2)* may not fully inform them of the importance of that setting. The added abstraction that makes *SPiCT* easier to operate with, from a developing perspective, may also obfuscate important decision steps that will be missed by those not yet well experienced on stock assessment. In an analysis made by a single user focusing in a single stock, this would be just a matter of an user being familiar with the tools being used. In the context of several methods being incorporated in a tool that is meant to be pushed into production and maintained by possibly several, however, this factor may result in an additional source of friction that should be accounted for.

It would appear at first that the domain of stock assessment does not offer many opportunities for the use of traditional Data Science approaches. Fisheries data seldom constitute a big data problem, more often than not trending towards the data-poor or data-starved end of the spectrum. Machine learning and deep learning approaches are typically more suited towards forecasting and prediction problems and their reduced focus on inference makes them undesirable for stock status discussion. Still, *CMSY++*'s use of a neural network to estimate the distribution range of some priors provides a good example of how deep learning can support the methodology without compromising the inference framework required. Other hybrid approaches have been put forward recently, such as using boosted gradient trees to correct estimates from a classical inference model [110] or incorporating Random Forests in the multivariate analysis of multispecific fisheries [111] (or, as a science news website put it, "New use for A.I.: Correctly estimating fish stocks! First-ever A.I. algorithm correctly estimates fish stocks, could save millions and bridge global data and sustainability divide" [112]. Over-enthusiasm aside, there appears to be space for classical stock assessment methods to be enhanced by data-science approaches.

Chapter 6

Conclusions

Through this work, it was successfully established a preliminary approach to apply some existing *SPM* and *GDM* methods to existing data for the octopus fishery data in Portugal. All 3 *SPM* approaches yielded somewhat consistent ranges for the maximum sustainable yield for the fishery in each region, but the variability in stock status assessment ranged from small, volatile stocks that are overfished (*CMSY*++) to massive stocks that are barely exploited (*SPiCT*). Moving forward, an approach that integrates seasonality, intra-annual variability and cephalopods' fast growth such as *CatDyn* is recommended. Such an approach, integrated with a more thorough examination of prior sensitivity of one of the considered methods and validation of the input series through consideration of alternative standardization scenarios may form the basis of a valid assessment for this fishery.

All considered methods were readily available, well documented, and they presented different degrees of difficulty to implement and deploy in automated environments. Ultimately, they all proved to be usable in a distributable tool such as the prototype *Shiny* app developed in this work. Integrating several methods in such a tool is an attractive prospect, allowing the user to test various scenarios and compare outcomes in real time. However, the high sensitivity all the methods displayed towards correct prior assumptions on the stock and the volatility on the stock scenarios they produced should be met with caution. A tool based on what extensive analysis may have determined to be the best methods may result in function as an abstraction layer that obfuscates the important analysis that correct stock assessment requires prior to the beginning of the modelling stage. If such a tool or app is ever commissioned, great care must taken not to streamline the functionality to the point where it leads the user towards poor results and poor decisions.

Appendix A

Results for the bottom trawl fleet

A.1 CMSY++

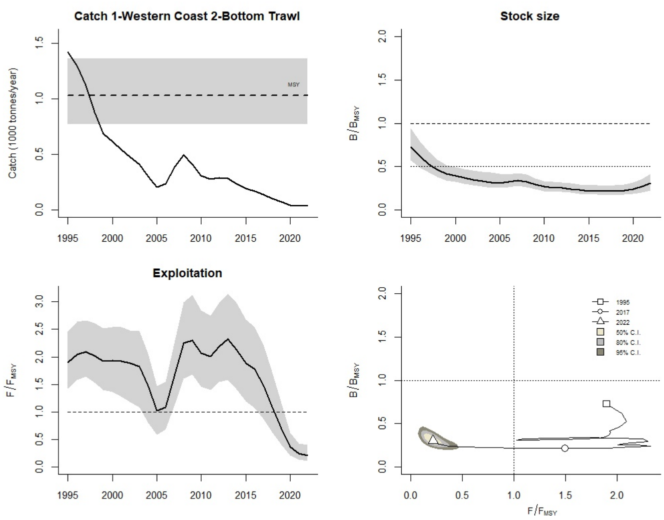


FIGURE A.1: Results from CMSY++ model fit or the Portuguese octopus landing by the bottom trawl fleet in the Western region of Portugal between 1995 and 2022: yearly catch (top left), MSY estimated biomass relative to the B_{MSY} (top right), estimated fishing mortality relative to the F_{MSY} (bottom left) and stock trajectory in terms of relative fishing mortality and relative biomass (bottom right).

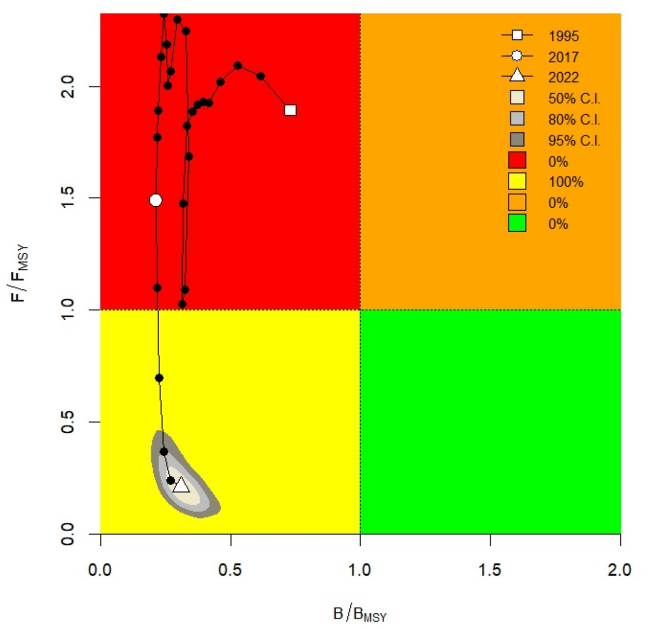


FIGURE A.2: Results from CMSY++ model fit for the Western octopus fishery by the bottom trawl fleet in Portugal: Kobe plot for the trajectory of the estimated relation between relative fishing mortality and relative biomass.

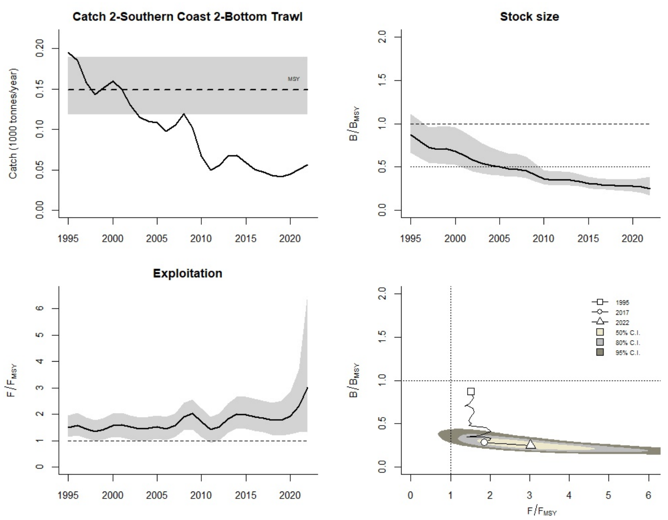


FIGURE A.3: Results from CMSY++ model fit for the Portuguese octopus landing by the bottom trawl fleet in the Southern region of Portugal between 1995 and 2022: yearly catch (top left), MSY estimated biomass relative to the B_{MSY} (top right), estimated fishing mortality relative to the F_{MSY} (bottom left) and stock trajectory in terms of relative fishing mortality and relative biomass (bottom right).

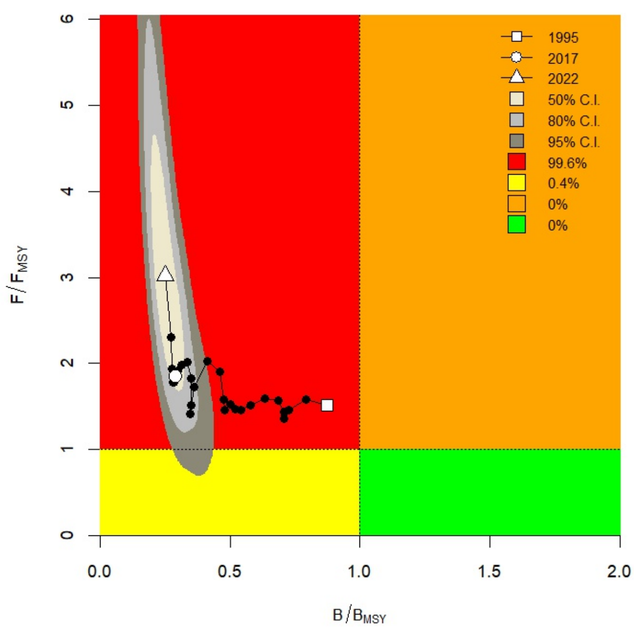


FIGURE A.4: Results from CMSY++ model fit for the Southern octopus fishery by the bottom trawl fleet in Portugal: Kobe plot for the trajectory of the estimated relation between relative fishing mortality and relative biomass.

A.2 JABBA

TABLE A.1: JABBA estimates for the octopus bottom trawl fishery in the Portuguese Western Coast in terms of media, lower confidence interval (lci), upper confidence interval (uci).

var	mu	lci	uci
K	8291233.08	5802743.07	12717024.62
r	0.08	0.04	0.16
psi	0.89	0.61	1.30
sigma.proc	0.05	0.03	0.10
m	1.00	1.00	1.00
Hmsy	0.08	0.04	0.16
SBmsy	3051698.65	2135776.79	4680670.10
MSY	264166.52	149040.61	378759.77
bmsyk	0.37	0.37	0.37
P1	0.89	0.61	1.31
P28	0.06	0.03	0.46
B_Bmsy.cur	0.18	0.08	1.25
H_Hmsy.cur	1.19	0.19	3.31

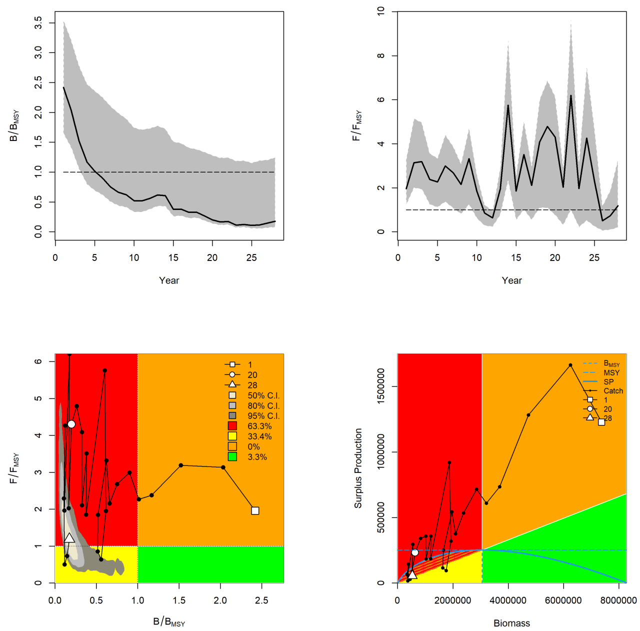


FIGURE A.5: JABBA surplus production model fit for the octopus bottom trawl fishery in the Portuguese Western Coast: yearly biomass estimates relative to the estimate for the BMSY estimate (top left), yearly fishing mortality relative to the estimate for the FMSY estimate (top right), Kobe plot (bottom left) and surplus production curve (bottom right).

TABLE A.2: JABBA estimates for the octopus bottom trawl fishery in the Portuguese Southern Coast in terms of media, lower confidence interval (lci), upper confidence interval (uci).

var	mu	lci	uci
K	1725092.76	877512.37	4248776.81
r	0.22	0.09	0.54
psi	0.95	0.62	1.31
sigma.proc	0.05	0.03	0.09
m	1.00	1.00	1.00
Hmsy	0.22	0.09	0.54
SBmsy	634943.34	322980.10	1563818.83
MSY	139429.50	76934.09	398885.84
bmsyk	0.37	0.37	0.37
P1	0.96	0.62	1.30
P28	0.82	0.47	1.02
B_Bmsy.cur	2.23	1.27	2.77
H_Hmsy.cur	0.18	0.06	0.56

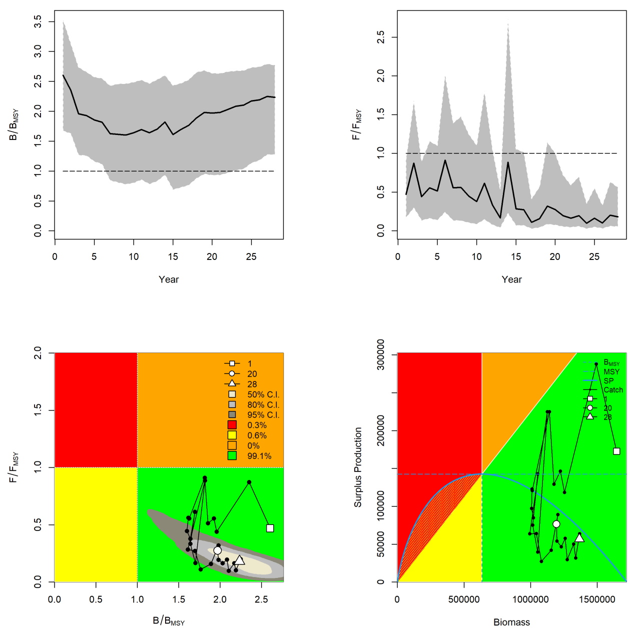


FIGURE A.6: JABBA surplus production model fit for the octopus bottom trawl fishery in the Portuguese Southern Coast: yearly biomass estimates relative to the estimate for the BMSY estimate (top left), yearly fishing mortality relative to the estimate for the FMSY estimate (top right), Kobe plot (bottom left) and surplus production curve (bottom right).

A.3 SPiCT

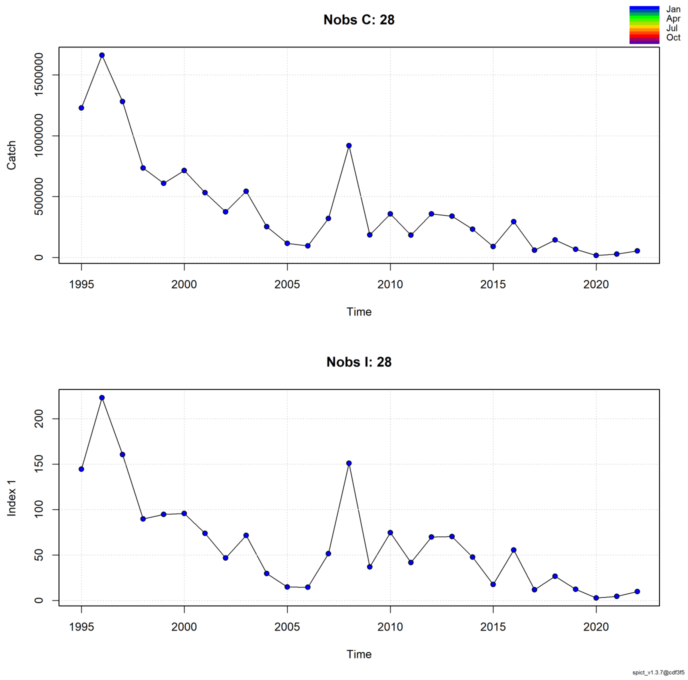


FIGURE A.7: Octopus catches (kg) and LPUE (Index 1) of the bottom trawl fleet in the Portuguese Western Coast between 1995 and 2022, aggregated by year, plotted with built-in SPiCT plotting functions.

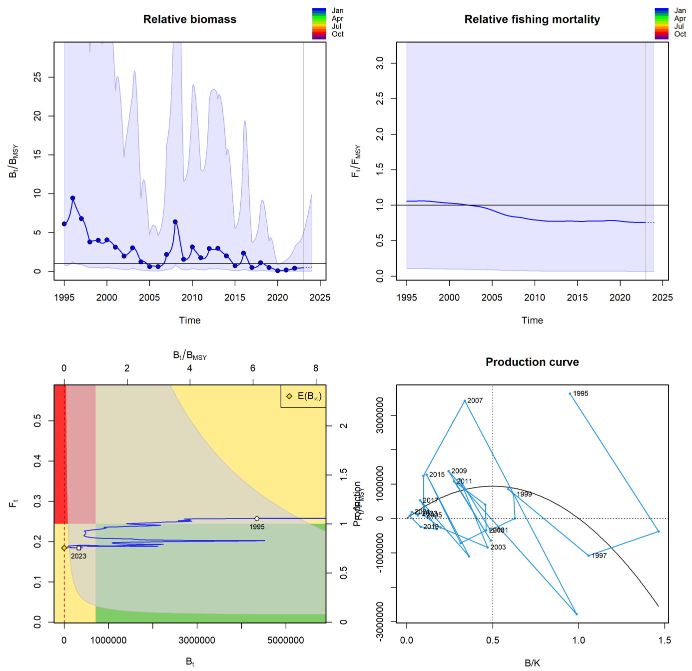


FIGURE A.8: Results from SPiCT model fit to the octopus fishery from the bottom trawl fleet in the Portuguese Western Coast between 1995 and 2022, aggregated by year: estimated biomass over BMSY (top left), estimated fishing mortality over FMSY (top right), Kobe plot with the fishing mortality vs biomass trajectory (bottom left) and surplus production curve with trajectory (bottom right).

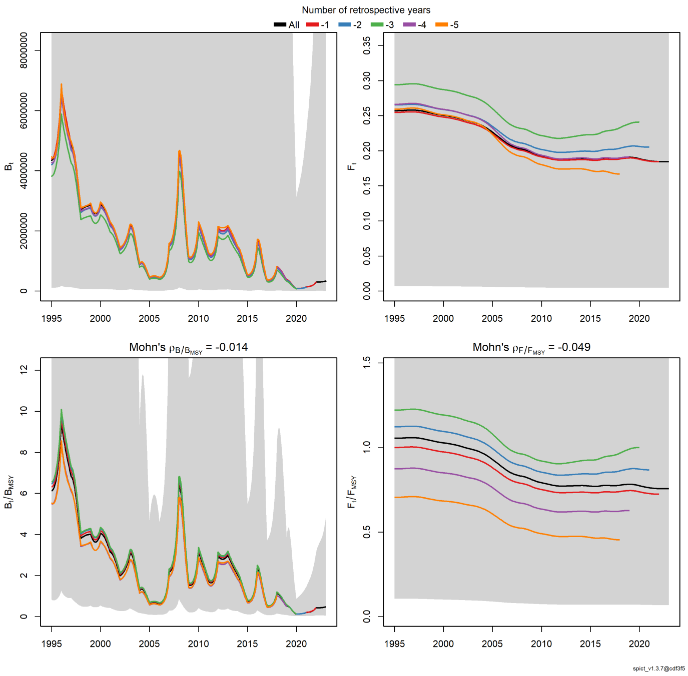


FIGURE A.9: Retrospective plots for the SPiCT model fit of the octopus fishery from the bottom trawl fleet in the Portuguese Western Coast between 1995 and 2022, aggregated by year.

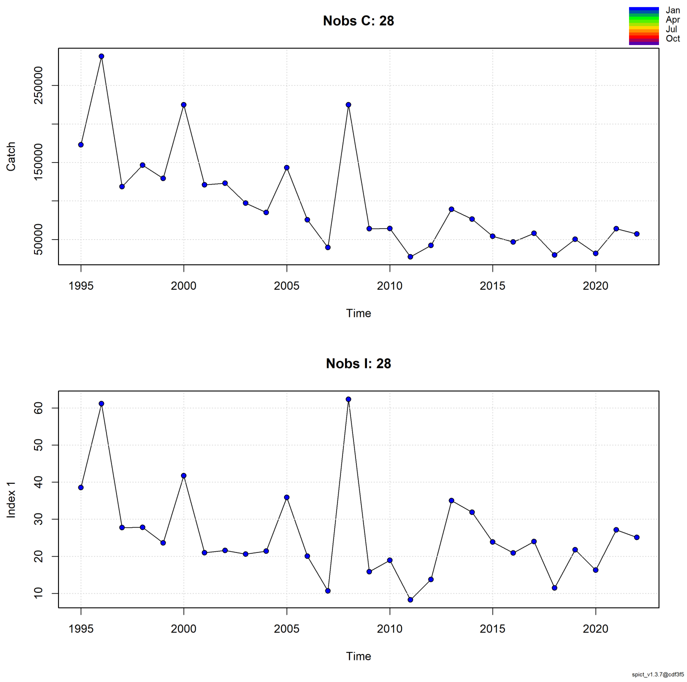


FIGURE A.10: Octopus catches (kg) and LPUE (Index 1) of the bottom trawl fleet in the Portuguese Southern Coast between 1995 and 2022, aggregated by year, plotted with built-in SPiCT plotting functions.

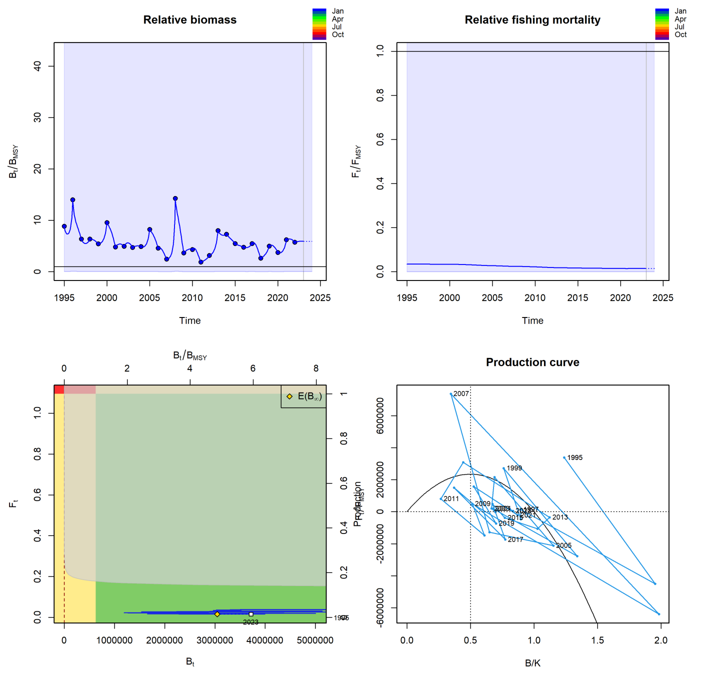


FIGURE A.11: Results from *SPiCT* model fit to the octopus fishery from the bottom trawl fleet in the Portuguese Southern Coast between 1995 and 2022, aggregated by year: estimated biomass over B_{MSY} (top left), estimated fishing mortality over F_{MSY} (top right), Kobe plot with the fishing mortality vs biomass trajectory (bottom left) and surplus production curve with trajectory (bottom right).

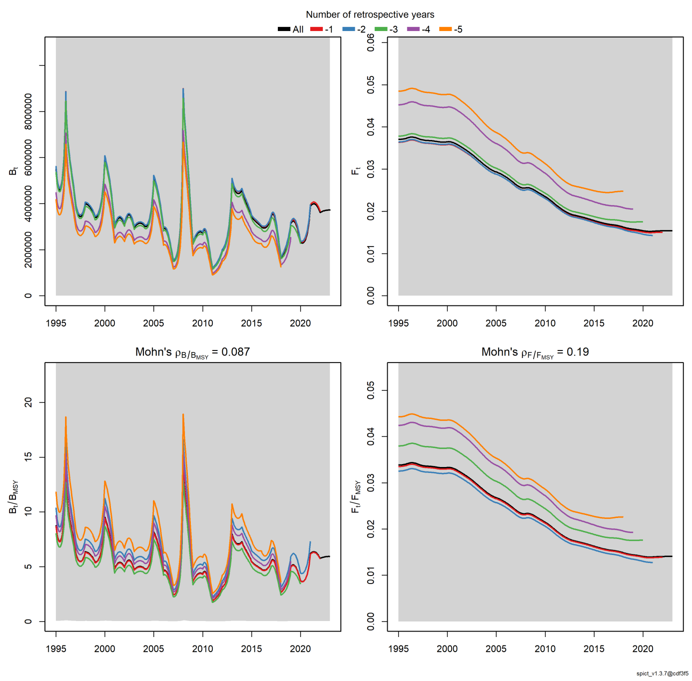


FIGURE A.12: Retroactive plots for the *SPiCT* model fit of the octopus fishery from the bottom trawl fleet in the Portuguese Southern Coast between 1995 and 2022, aggregated by year.

TABLE A.3: Parameter estimates from the *SPiCT* model fit to the octopus landings from the bottom trawl fleet in the Western region of Portugal, in terms of estimates (estimate and log.est), lower confidence interval (cilow) and upper confidence interval (ciupp).

parameter	estimate	cilow	ciupp	log.est
alpha	0.04	0.00	66.27	-3.11
beta	4.34	0.91	20.78	1.47
r	0.82	0.25	2.68	-0.20
rc	0.82	0.25	2.68	-0.20
rold	0.82	0.25	2.68	-0.20
m	939800.89	96571.02	9145866.76	13.75
K	4576601.51	213338.21	98178763.69	15.34
q	0.00	0.00	0.00	-10.31
sdb	0.85	0.62	1.15	-0.17
sdf	0.07	0.02	0.29	-2.62
sdi	0.04	0.00	53.43	-3.27
sdc	0.31	0.19	0.52	-1.16
Bmsys	710005.57	71098.39	7090285.87	13.47
Fmsys	0.24	0.03	1.81	-1.41
MSYs	-	-	-	-

TABLE A.4: Parameter estimates from the *SPiCT* model fit to the octopus landings from the bottow trawl fleet in the Southern region of Portugal in terms of estimates (estimate and log.est), lower confidence interval (cilow) and upper confidence interval (ciupp).

parameter	estimate	cilow	ciupp	log.est
alpha	0.05	0.00	76.43	-3.01
beta	2.29	0.96	5.50	0.83
r	2.11	0.83	5.33	0.75
rc	2.11	0.83	5.33	0.75
rold	2.11	0.83	5.33	0.75
m	2348627.17	223.81	24646039544.21	14.67
K	4456182.02	427.18	46485415182.64	15.31
q	0.00	0.00	0.08	-11.88
sdb	0.82	0.54	1.26	-0.19
sdf	0.11	0.06	0.23	-2.18
sdi	0.04	0.00	57.37	-3.20
sdc	0.26	0.16	0.43	-1.35
Bmsys	626980.03	17.18	22883975101.53	13.35
Fmsys	1.10	0.21	5.83	0.09
MSYs	752202.05	72.38	7817200234.20	13.53

A.4 Summary

TABLE A.5: Parameter estimates from each framework after fitting variations from several surplus production models to the Portuguese bottom trawl fishing data on octopus in the Western region of Portugal. Parameters labeled with *(a)* refer to estimates for the final year in the series (2022).

Model Parameter	units	CMSY++ CMSY	CMSY++ BSM	JABBA Fox	SPiCT -
q	adim.	-	3.77	≈ 0	≈ 0
mp	adim.	-	-	1.00	-
r	adim.	0.656	0.447	0.08	2.11
K	1000 tons	5.81	8.93	8.3	4.4
MSY	1000 tons	0.953	1.01	0.26	0.7
F_{MSY}	adim.	-	0.304	0.08	1.1
B_{MSY}	1000 tons	-	7.32	3.0	0.6
B/B_{MSY} (a)	adim	-	0.306	0.18	-
B/K (a)	adim.	0.104	0.104	*	-
F (a)	adim.	-	0.306	*	-
F/F_{MSY} (a)	adim.	-	0.03	1.19	-
$F/r/2$ (a)	adim.	0.565	2.64	*	-

TABLE A.6: Parameter estimates from each framework after fitting variations from several surplus production models to the Portuguese bottom trawl fishing data on octopus in the Southern region of Portugal. Parameters labeled with *(a)* refer to estimates for the final year in the series (2022).

Model Parameter	units	CMSY++ CMSY	CMSY++ BSM	JABBA Fox	SPiCT -
q	adim.	-	0.426	≈ 0	≈ 0
mp	adim.	-	-	1.00	-
r	adim.	0.64	0.553	0.22	0.29
K	1000 tons	0.98	1.08	1.7	4.4
MSY	1000 tons	0.157	.149	0.1	7.57
F_{MSY}	adim.	-	0.138	0.22	0.14
B_{MSY}	1000 tons	-	0.54	0.6	55.7
B/B_{MSY} (a)	adim	-	0.25	0.23	-
B/K (a)	adim.	0.193	0.193	*	-
F (a)	adim.	-	0.418	*	-
F/F_{MSY} (a)	adim.	-	3.02	0.18	-
$F/r/2$ (a)	adim.	1.3	0.99	*	-

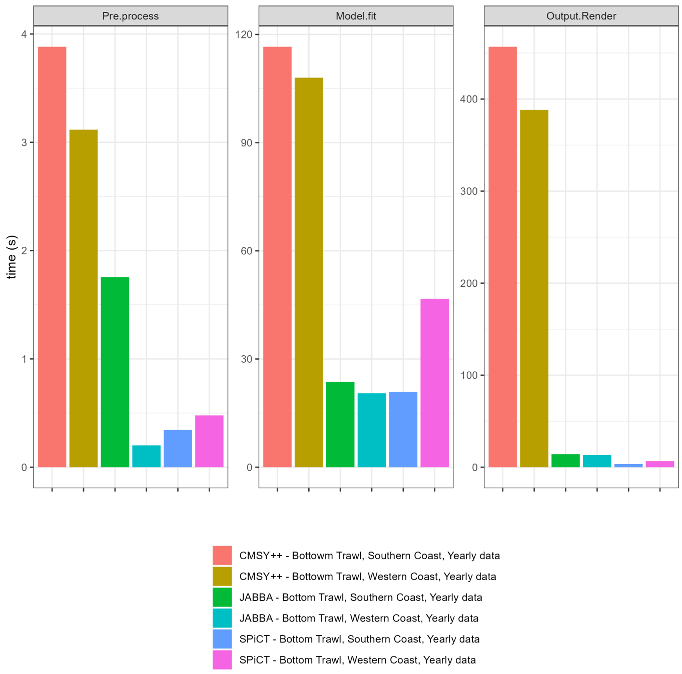


FIGURE A.13: Performance times, in seconds, of each framework at each stage of fitting a surplus production model to the Portuguese bottom trawl fishing data on octopus in the Western and Southern regions of Portugal.

Appendix B

Supplementary Material

B.1 CatDyn

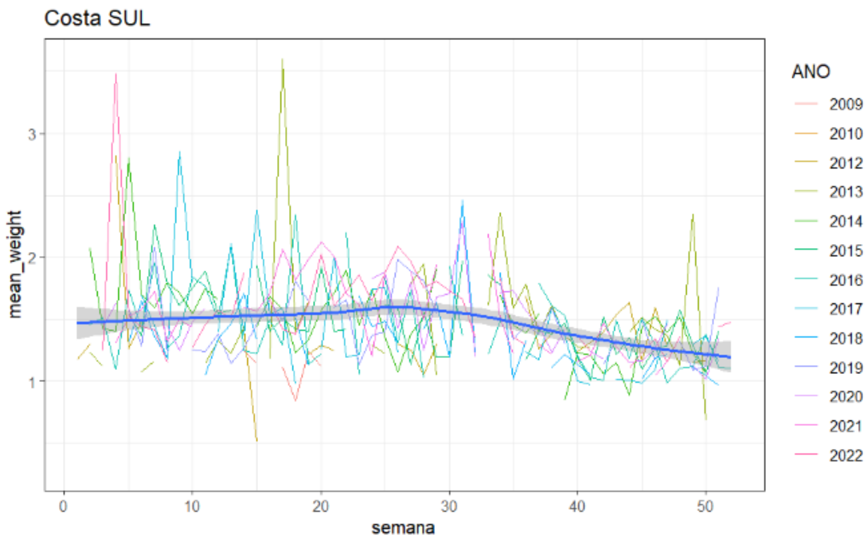


FIGURE B.1: Weekly variation of mean body weight of octopus individuals, by year, estimated from samples from the polyvalent fleet operating in the Southern region of Portugal between the years of 2009 and 2022 [106].

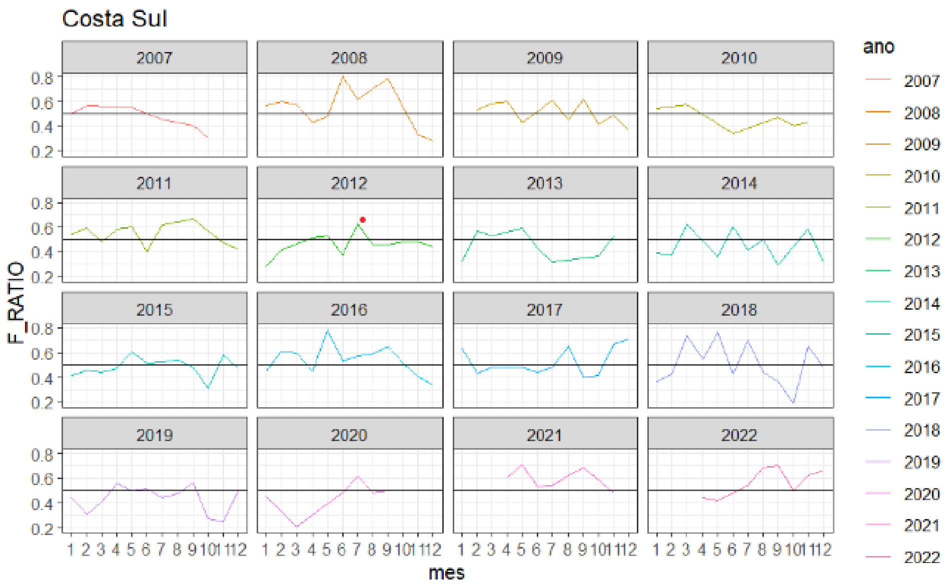


FIGURE B.2: Monthly variation of the female ratio in octopus samples, by year, estimated from samples from the polyvalent fleet operating in the Southern region of Portugal between the years of 2009 and 2022 [106].

Appendix C

Results for the polyvalent fleet

C.1 JABBA

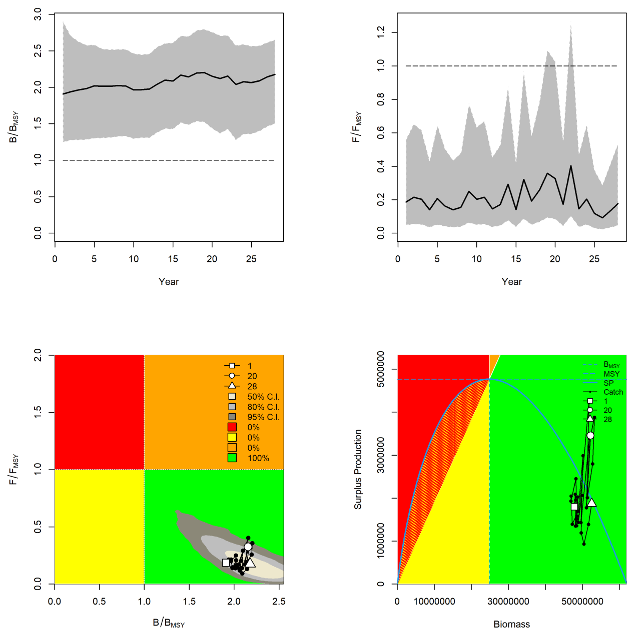


FIGURE C.1: JABBA surplus production model (Pella-Tomlinson) fit for the octopus polyvalent fishery in the Portuguese Western Coast: yearly biomass estimates relative to the estimate for the B_{MSY} estimate (top left), yearly fishing mortality relative to the estimate for the F_{MSY} estimate (top right), Kobe plot (bottom left) and surplus production curve (bottom right).

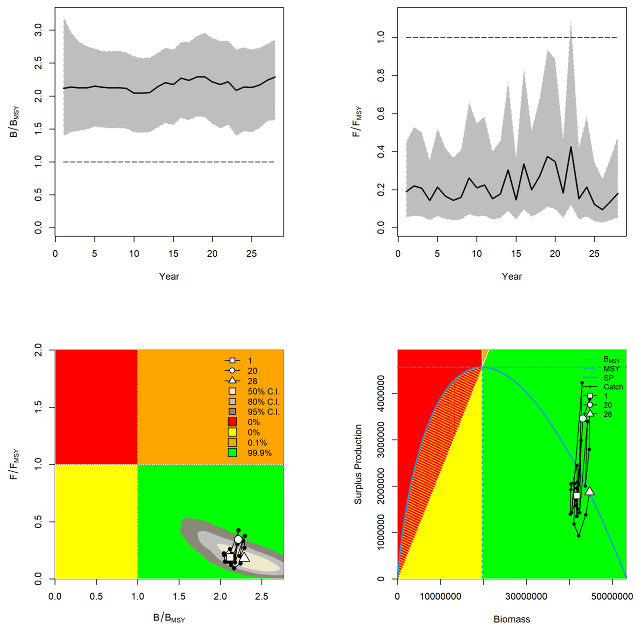


FIGURE C.2: JABBA surplus production model (Fox) fit for the octopus polyvalent fishery in the Portuguese Western Coast: yearly biomass estimates relative to the estimate for the B_{MSY} estimate (top left), yearly fishing mortality relative to the estimate for the F_{MSY} estimate (top right), Kobe plot (bottom left) and surplus production curve (bottom right).

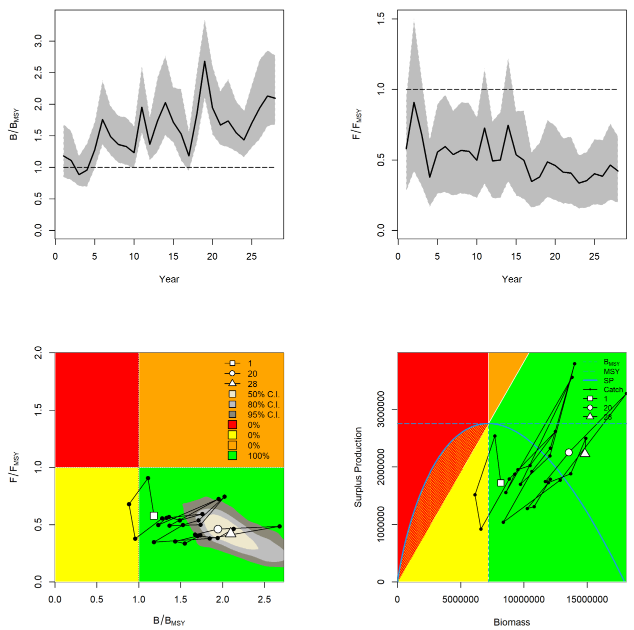


FIGURE C.3: JABBA surplus production model (Pella-Tomlinson) fit for the octopus polyvalent fishery in the Portuguese Southern Coast: yearly biomass estimates relative to the estimate for the B_{MSY} estimate (top left), yearly fishing mortality relative to the estimate for the F_{MSY} estimate (top right), Kobe plot (bottom left) and surplus production curve (bottom right).

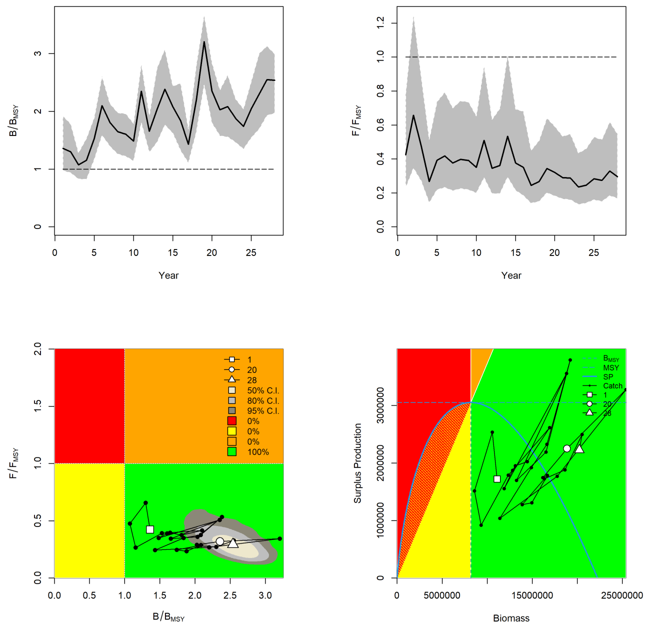


FIGURE C.4: JABBA surplus production model (Fox) fit for the octopus polyvalent fishery in the Portuguese Southern Coast: yearly biomass estimates relative to the estimate for the B_{MSY} estimate (top left), yearly fishing mortality relative to the estimate for the F_{MSY} estimate (top right), Kobe plot (bottom left) and surplus production curve (bottom right).

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