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Regional stock assessment of the flying jumbo squid in the South-Eastern Pacific

CALAMASUR

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Contents

Executive Summary

The flying jumbo squid fishery is the largest invertebrate fishery in the world and one of the largest of the world even when including finfish fisheries. In the South East Pacific Ocean (SEP) it is fished in four regions: Ecuadorian, Peruvian and Chilean exclusive economic zones (EEZ), and international waters off those EEZs. In international waters, the main operators currently are China (mainland and Taiwan) and South Korea. During this year, efforts have been made toward sharing and standardising databases among countries fishing jumbo squid in the SEP and a common regional framework for stock assessment on the SEP have been proposed. A recent review of stock assessment for cephalopod fisheries argued that the best approach to assess cephalopod stocks involves innovative depletion models.

A stock assessment database was built to apply multi-annual depletion models combined with surplus production models from monthly catches and fishing effort of the Asian fleets, and monthly catches, fishing effort and mean fish weight of squids in the catch by Chilean fleets, spanning January 2011 to December 2021. The stock assessment took into account environmental cycles in the SEP with models having time-varying parameters. A hierarchical statistical inference framework connected biomass predictions of multi-annual depletion models with the surplus production model, which took the Pella-Tomlinson form. Given the lack of Peruvian data, one accessory model provided biomass estimations from Peruvian EEZ using published data.

The biomass dynamics of the stock in the region is driven by environmental cycles connected to the ENSO, leading to changes in the carrying capacity of the environment, the symmetry of the production function, and the intrinsic rate of population growth. The largest change occurs in the intrinsic rate of population growth, which increases 62% during the ENSO period. During warm, ENSO years the stock has higher sustainable harvest rates and wider fluctuations than during normal, cold water periods. The low end of these biomass fluctuations are cause of concern for the sustainability of the fishery.

Nevertheless, actual harvest rates during warm, ENSO years as well during cold, normal periods, have been well below the sustainable harvest rates of each period. This result combined with high escapement biomass at the end of the last season in the time series (2020) indicates that the stock is not over-fished and not undergoing over-fishing.

Results from this stock assessment methodology can be improved substantially by a collaborative effort with Chinese, Peruvian and Ecuadorian experts to compile a more complete database of monthly catch, fishing effort and mean weight. The published academic literature indicates that biological data from the Chinese fleet, the largest and the one covering the larger part of the stock distribution, are available.

1 Introduction

The flying jumbo squid *Dossiduscus gigas*) fishery extends over the whole Eastern Pacific Ocean yielding the largest volume of landings of any invertebrate fishery worldwide, reaching over a million tonnes in recent years [1]. This species is widely distributed in the Eastern Pacific, ranging approximately from 45^o N to 45^o S along the continental slope and extending to oceanic waters on the south east pacific up to 140^oW [2], inhabiting from the surface down to depths of 1200 m [3]. The highest abundance of flying jumbo squid are found off Peruvian and Chilean coasts. According to FAO records [4], in the South Eastern Pacific Ocean (SEP) the fishery started to develop and grow in the early 90s, with the activities of Japanese and Korean fleets in international waters off the jurisdiction of Ecuador, Peru and Chile, and Peruvian fleets in Peru's Exclusive Economic Zone (EEZ). Starting in the 2000s, Chilean and Chinese fleets joined the exploitation in Chilean EEZ and international waters, respectively, and in 2014 Ecuadorian fleets became active in the fishery with landings in the low thousands.

During the last decade, biological attributes regarding age and growth [5], reproduction [6], mortality [7], feeding [8], predators [9], and the connection between volume of catches and environmental conditions [10, 1] have been reported. In recent years, discussions regarding method to assess jumbo squid and efforts toward sharing and standardizing databases have been made among countries fishing jumbo squid in the SEP [11, 12], including a first attempt for a conceptualisation [13] and implementation [14] of region-wide stock assessment. In spite of these efforts, there is still need of an integrated system of observation, assessment and management to secure the continued viability of the fishery [15]. Currently, there is much interest in generating scientific knowledge leading to an assessment of the abundance and productive capacity of the stock in the SEP region as a whole. This knowledge would be useful to take coordinated and agreed upon management actions aimed at the sustainable exploitation of the stock by the various fleets and countries involved.

Life history and stock dynamic of cephalopods differ for many harvested fish populations which imposes challenges for assessing and manage their populations [16]. Cephalopods are commonly characterised by very fast growth rates, short life span, high fecundity, continuous spawning during a given season. In addition most of cephalopods are semelparous [17], an individual undergoes only a single reproductive cycle after which it dies. Some cephalopods like the jumbo squid exhibit high migratory behaviour [18, 3] and age is difficult to asses given the formation of daily increments in hard structures such statolihts. From an assessment viewpoint, in semelparous and fast-growing animals, the estimation of natural mortality become extremely challenging. On the other hand, the time consuming-nature of reading daily increments in cephalopods hard structures make age-based models impractical to be used in the context of stock assessments [16]. In addition, fishery-independent surveys to assess population abundance are also impractical to be use in jumbo squid given the spatial scale of its distribution. Capture per unit of effort (CPUE) is usually used as abundance index in fisheries where fisheries-independent abundance indices are lacking. However, even the use of standardised CPUE is not recommended for highly migratory and fast-growing animals such as jumbo squid [16]. These characteristics preclude the application of routine assessment methods usually applied in teleost fishes which are commonly based on cohort analyses in which abundance indices are derived from surveys and/or standardised CPUE. In this context, Arkhipkin et al. [16] conducted an updated review of cephalopods stock assessment and management and recommended the use of depletion models running at rapid time steps. Such family of stock assessment models can handle rapid life history with short life span in which aging and fishery-independent data are not required and natural mortality can be estimated within the stock assessment model. Roa-Ureta et al. [19, 20, 21, 22] have presented a non-Bayesian hierarchical statistical method that combines results from generalized depletion models with generalized surplus production models to assess stocks of data-limited fisheries fisheries leading to fully analytical assessments for data-poor and data-limited fisheries. Generalized depletion models are open population models that are particularly useful in the context of jumbo squid given its trans-zonal and long migratory behaviour. These depletion models are based on a mechanistic conceptualisation for the relationship between fishing effort and fish abundance as causes and fishing catch as result, thus overcoming limitations of linear approximations that use the CPUE to generate indices of abundance index.

In addition to all these challenges described above, the flying jumbo squid also show high phenotypic plasticity as a result of changes in environmental conditions [16]. Changes in the environmental conditions at the Humboldt current ecosystem (HCE) as a result of El Niño/ la Niña events have been associated with variations in growth, size at maturation and fecundity [23] and the spatio-temporal distribution of the jumbo squid [24]. Specific mechanisms on how environmental conditions are expressed in phenotypic plasticity are largely unknown, although hypotheses on how environmental temperature controlling egg size, fecundity and recruitment success have been discussed in the context of invertebrates inhabiting the HCE [25]. High phenotypic plasticity further complicates assessment and management of fishing resources because important individual attributes such as growth and fecundity will modify the productive capacity of a stock and thus resilience to fishing exploitation. In terms of fishing management, this means that Maximum Sustainable Yield (MSY) and other derived biological reference points (BRP) will also change with environmental attributes. For example, Lima el at. [26] proposed that environmental cycles played a key role in the collapse of the jack mackerel at the HCE given the mismatch of managing a population with changing productivity with environment under a fixed management framework.

The main aim of this technical paper, presented to the 2022 SC SPRFMO Meeting, is to assess the jumbo squid in the SEP region using Asian fleets and Chilean fleets catch and effort data at the monthly time step over the last decade, and Peruvian annualised CPUE data over the last two decades. The model implemented is a generalised depletion model [27, 28, 19, 20, 21, 22] combined with Pella-Tomlinson surplus production model in the hierarchical statistical inference method of Roa et al [19]. At the level of the surplus production model we take into account environmental cycles caused by El niño / La niña events by estimating models with time-varying parameters.

2 Materials and Methods

2.1 Regional Database

To apply the depletion model described in the next section, the database that needs to be compiled and curated by Ecuadorian, Peruvian, Chilean, Chinese mainland, Chinese Taiwan, and Korean fleets, consists of complete monthly landings and fishing effort, plus samples of mean weight of jumbo squids in the landings. Chilean fleets data were complete while Asian fleets data were complete in terms of landings and fishing effort while lacking in biological sampling data. Peruvian data were completely unavailable despite an official request to Peruvian authorities. Ecuadorian data were kindly provided by the Instituto Público de Pesca y Acuicultura (IPIAP) but these data were not included in this assessment because the Ecuadorian jumbo squid fishery officially started in 2014 while the available data only covered from 2018 to 2020. Moreover, the data from 2019 were incomplete, missing four months of fishing. The absence of Peruvian data was overcome by digitising plots published in reports. Therefore, this assessment covers the whole fishery area in the South Eastern Pacific Ocean (SEP) except the area corresponding the Exclusive Economic Zone of Ecuador. A detailed description of the available data is provided in the following sub-sections.

2.1.1 Asian fleets data

These data were provided by the South Pacific Regional Fisheries Management Organisation (SPRFMO) and consisted in monthly catches and effort measurement of Chinese mainland, Chinese Taiwan and Korean fleets from January 2012 to December 2020. These data were not fully dis-aggregated. Instead, individuals fishing hauls were aggregated by geographic blocks of degrees of latitude and longitude.

The Asian fleets database contained both total catch in kg as well as retained and discarded catch in kg, the latter in very small quantities. In fact over 92.5% of all entries had zero discarded catch and total discarded catch accounted for 0.0013% of total catch across the time series. Nevertheless, we used the total catch (addition of retained and discarded catch) for stock assessment purposes.

The Asian fleets database included seven potential measures of fishing effort, namely the number of vessels (from a minimum of three to a maximum of 365), number of singles jigs (0 to 5,654), number of double jigs (0 to 54,235), number of jigs per line (0 to 18,351), number of hours of fishing (0 to 33,496), total power (0 to 619078 kw), number of crew (0 to 31,928) and number of days of fishing (three to 4,397).

The spatial extension of the fishing by these fleets was vast, spanning 32 degrees of latitude and 50 degrees of longitude across the SEP. The Chinese mainland fleet was the largest of the three Asian fleets by far, accounting for 2,692 of the total number of 3,181 entries in the database, and displaying on average 1,064 vessels per month versus just 12 vessels per month in the Chinese Taiwan and Korean fleets.

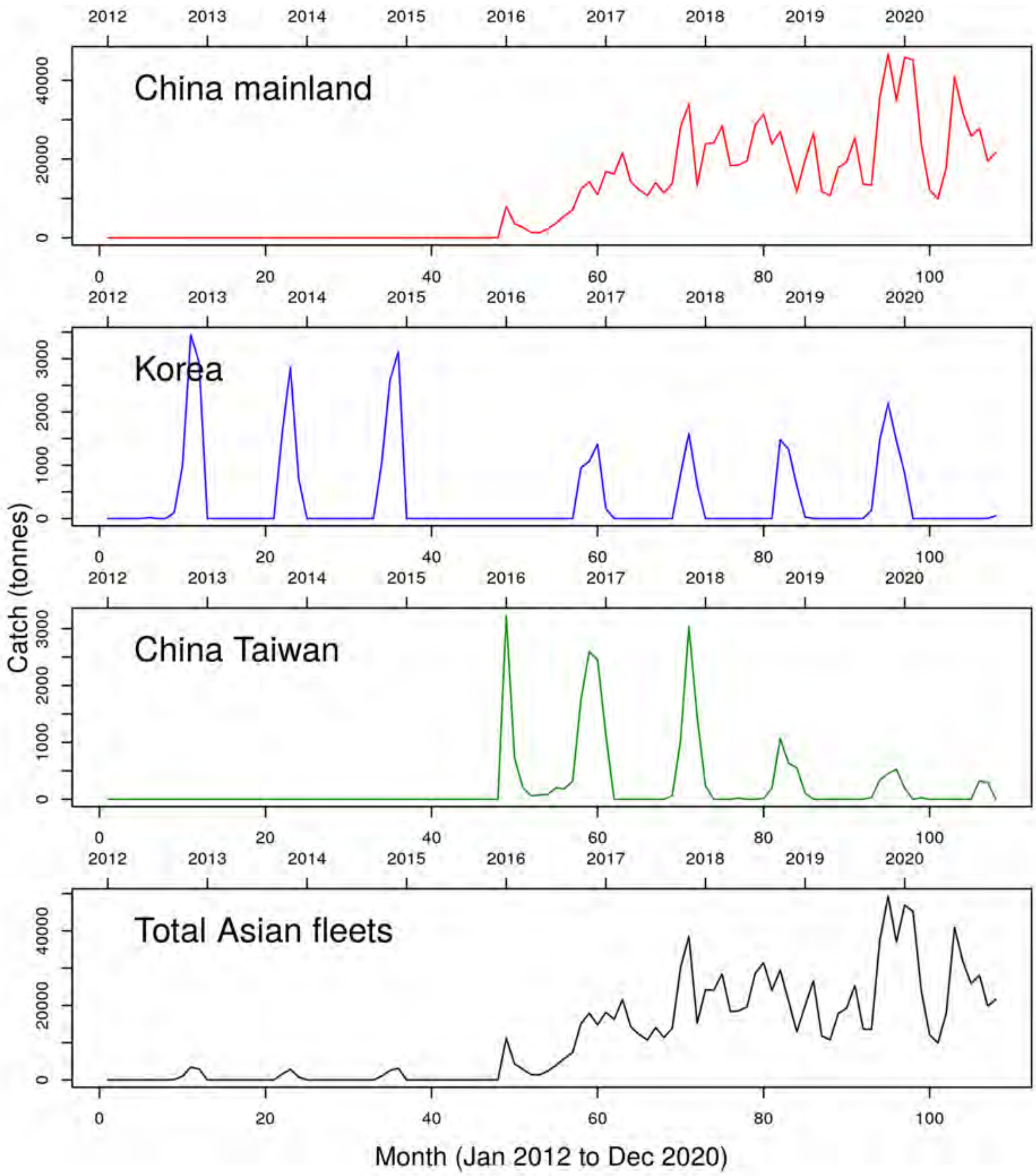

Figure 1: Time series of monthly catches reported by the three Asian fleets. Note the much larger scale of the y-axis in the China mainland panel.

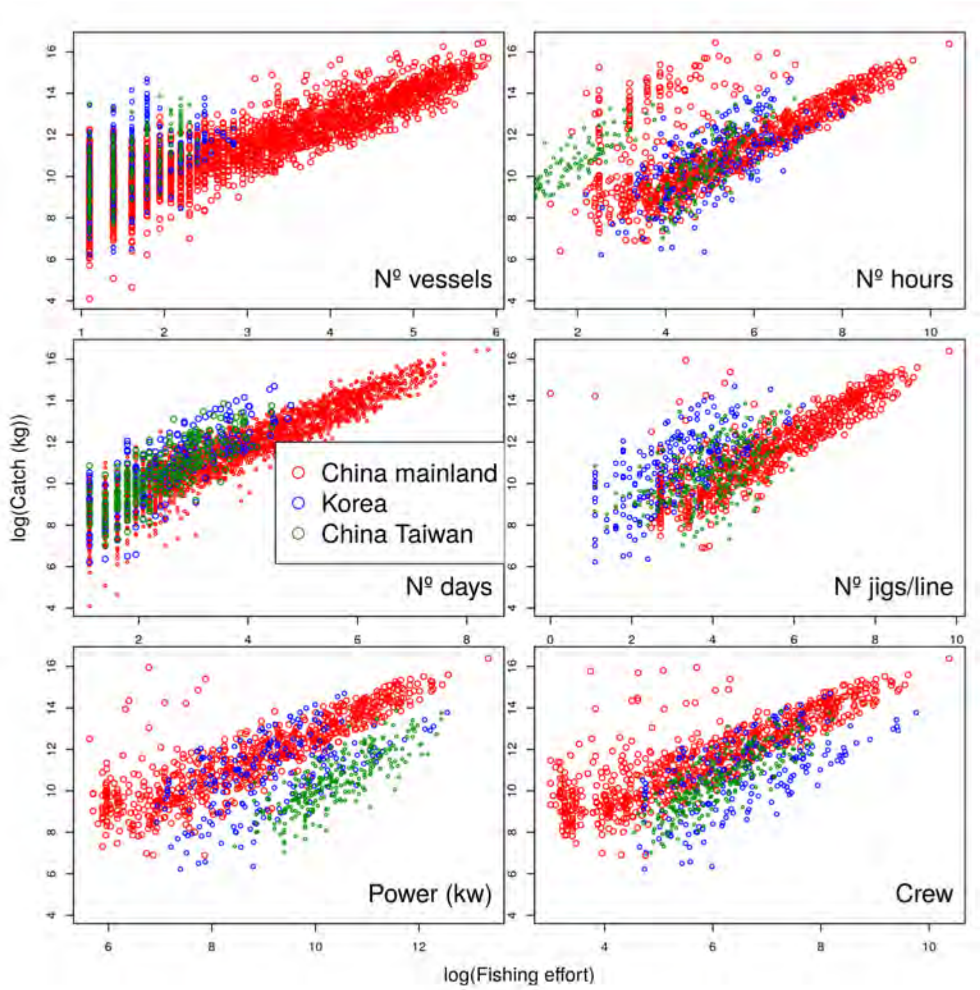

Figure 2: Catch and effort (log-log scale) of the three Asian fleets across different measurements of effort.

The Asian database did not include any biological data and yet mean weight by month data is necessary to implement stock assessment models used in this work. We took the length frequency data and length-weight data published by Liu et al. [29] and Ibanẽz and Cubillos [3] to calculate the mean weight per month of season of the year. The former work uses relatively large samples taken over a number of years of the operation of the Chinese fleet while the latter work presents data on seasonal variation of length frequencies in international waters off the Chilean EEZ. Then we used the length weight relationship to transform mean mantle lengths to mean whole body weight per season of the year and the corresponding standard errors of those mean weight. Finally we used these mean weight and their standard errors per season of the year to predict the mean weight per month in the catch of the Asian fleets along the entire time series spanning January 2012 to December 2020. We did that with a re-sampling algorithm from truncated normal distributions using R package Runuran [30].

2.1.2 Chilean fleets data

A database of detailed logbook records from the industrial and artisanal fleets targeting jumbo squid in EEZ off Chile were provided by the Instituto de Fomento Pesquero (IFOP) upon requests directed to Chilean fishing authorities. These data consisted of dis-aggregated, haul-by-haul results of fishing for each fleet, including large samples of mantle length and whole body weight from quids in the catch, from January 2011 to December 2021. All fishing was conducted over the narrow continental shelf off central Chile inside the Chilean EEZ.

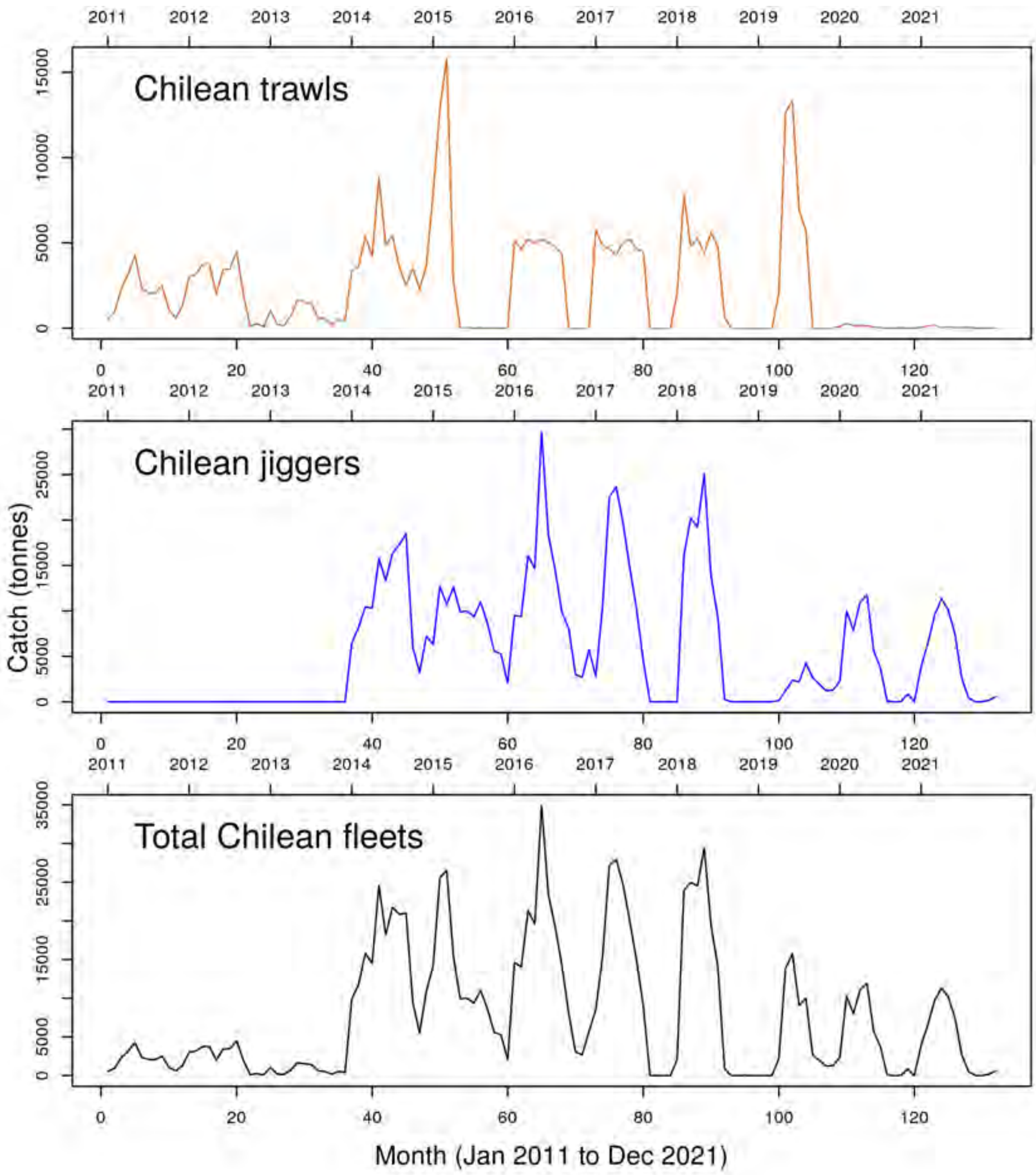

Figure 3: Time series of monthly catches reported by Chilean Fleets.

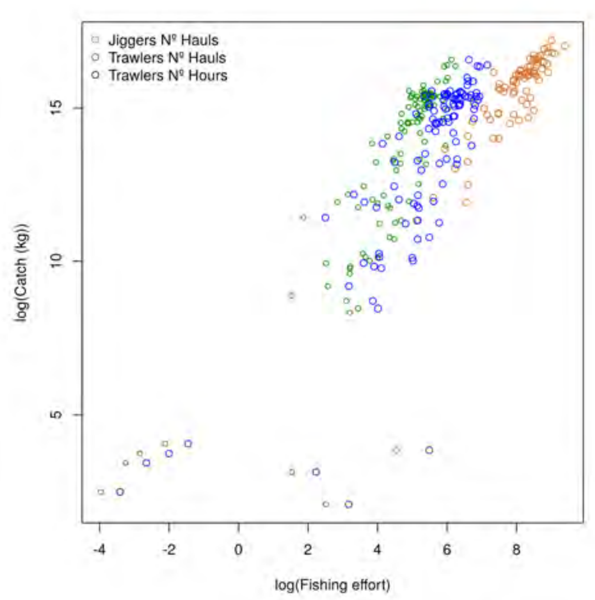

Figure 4: Catch and effort (log-log scale) of the Chilean fleets in hauls for jiggers and hauls and trawling hours trawls.

The fishing by the industrial fleet was conducted by trawling, starting in January 2011 and extending until December 2021, although it decreased substantially in 2020, to just 3.5% of the mean annual catch from 2011 to 2019, due to new legislation making the jumbo squid a resource reserved for the artisanal sector. The fishing by the artisanal fleet was conducted by jigging, starting in January 2014 and extending until December 2021.

2.1.3 Peruvian fishery

As stated previously, it was not possible to obtain detailed Peruvian fleets data as requested by our team in April 2022. However, considering that the Peruvian area is very important at the regional level and that Peruvian fleets report very large landings, we considered it very much worthwhile to incorporate the Peruvian fraction of the stock in some objective manner within our modelling framework. So instead of starting with raw Peruvian data to fit a stock assessment model, we estimated the biomass of the stock in the Peruvian EEZ using their published reports and then added that biomass to the stock biomass estimated from raw data from the Asian and Chilean fleets fishing in international and Chilean EEZ waters, respectively. These three stock biomass estimates were then included in a regional stock assessment as detailed in the following section.

To estimate stock biomass in the Peruvian EEZ we downloaded the last official and freely available stock assessment report from the Peruvian government website, namely from *Ministerio de la Producción* PRODUCE (`https://www.gob.pe/produce`). This official report for stock assessment presented figures and tables with annual catches, nominal CPUE (in number of individuals per fishing trip) and mean weight in the landing from 2000 to 2021. This information was digitised and each data point was extracted. CPUE in tonnes per fishing trip where then computed using the mean weight, also reported. Digitised data and the derived annual CPUE values are presented in Fig. 5.

Figure 5: Digitised Peruvian data for landings, mean individual weight, CPUE in number of individuals per fishing trip and computed CPUE in tonnes per fishing trip.

Figure 6: Comparison of the times series of digitised estimates biomass in Peru and the stock assessment implemented

A Pella-Tomlinson biomass dynamic model was implemented in JABB [31] using landings and CPUE (tonnes per fishing trip) so as to match the estimates provided in their official stock assessment in [32]. Fig. 6 shows our estimates of biomass from JABB and the digitised biomass time series from PRODUCE, demonstrating strong consistency between the official Peruvian estimates for abundance and our implemented model.

2.1.4 Spatial extension of Asian and Chilean fleets

Asian and Chilean data included spatial location of fishing hauls, at the individual haul level in the case of Chilean fleets and at the latitude-longitude spatial block level in the case of the Asian fleets. This allows understanding the spatial extension and expected degree of connectivity between the stock's fraction exploited by Chilean and Asian fleets.

Fig. 7 shows that Asian fleets in the SEP operate over a very large off the Ecuadorian, Peruvian and Chilean EEZs and in international waters extending far to the west following the equatorial meridian. Catches are relatively high even at the extreme western limit of operations but most of the largest catches occur off Perú and northern Chile.

Fig. 7 also shows that Chilean fleets operate mostly in the central-south part of the country's EEZ, and that their fishing grounds are separated from Asian fleets fishing grounds by a vast extension of waters off northern Chile.

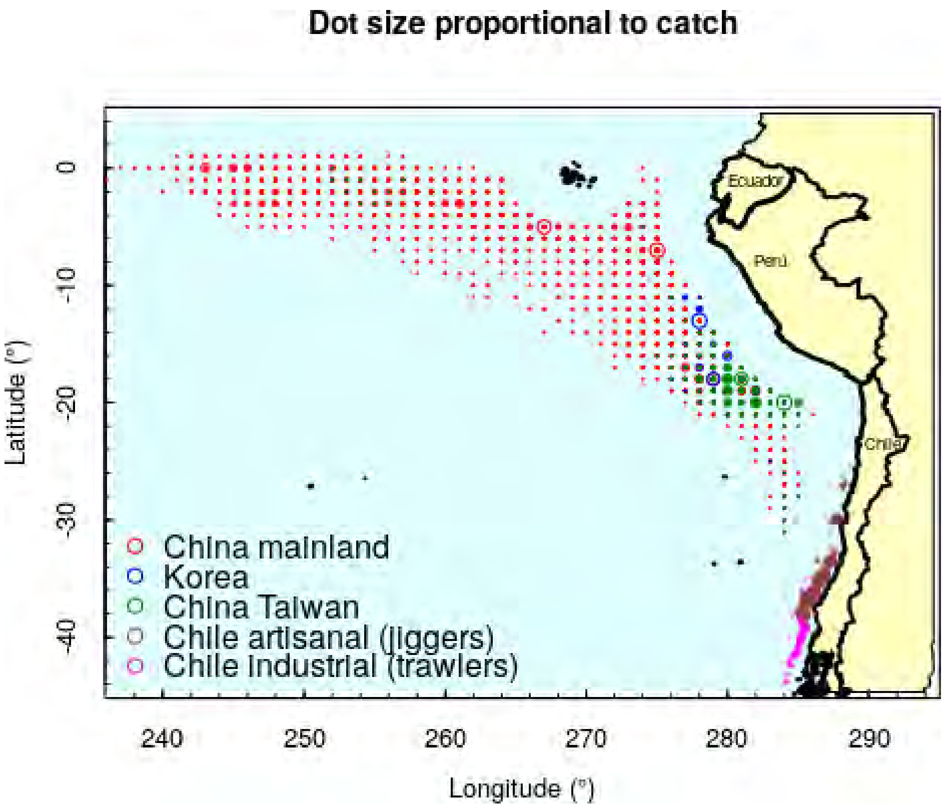

Figure 7: Spatial distribution of fishing effort by Asian and Chilean fleets.

2.2 Stock assessment

The general approach to the stock assessment of the jumbo squid stock in the South-East Pacific is portrayed in schematic fashion in Fig. 8. According to NOAA's El Ninõ indices 1 + 2 [33], a normal waters, cold period occurred from 2000 to 2013, while in 2014 an El Niño period started and extended until the last year of our time series (2020). Therefore we set up 2014 as a regime shift year to fit stock assessment models that recognized these environmental cycles.

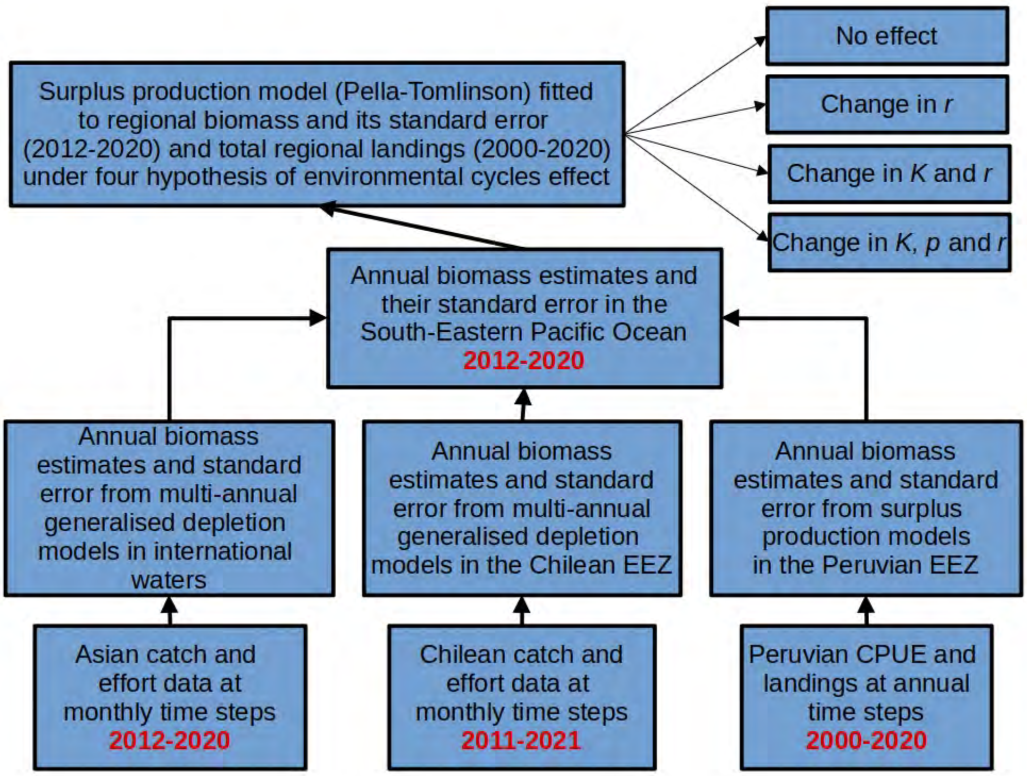

Figure 8: Schematic representation of the stock assessment modelling approach. At the base level, raw data of monthly catch, fishing effort and mean weight in the catch are compiled for the Asian and Chilean fleets, and annual CPUE and landings from the Peruvian fleets. At the intermediate level, Asian and Chilean raw data are used to fit separately, one-fleet generalised depletion models in R package CatDyn, and a surplus production model from Peruvian published stock assessments reports. At the top level, all three biomass estimates and their standard errors as well as the total regional landings time series are used to fit a regional Pella-Tomlinson surplus production model. The hierarchical inference method propagates statistical uncertainty from the basal to the top level. At the top level, four alternative hypotheses are tested: constant parameters (null hypothesis) and three alternative hypotheses where parameters K, p and r vary singly or in pairs or trios from warm to cold water regimes.

2.2.1 Generalised depletion models

Generalised depletion models are depletion models for open populations with nonlinear dynamics. Regarding the open population aspect, traditional depletion models do not admit inputs of abundance during the fishing and that is the reason they could not be used for multi-annual assessments, since in that case one obvious factor, the annual pulse of recruitment, could not be included in the assessment. Therefore, depletion models were often connected to assessing stocks with intra-annual data, for one season of fishing separately. Generalised depletion models allow any number of exogenous inputs of abundance during the fishing, so they are apt for multi-annual assessments with monthly data [28]. Regarding the nonlinear dynamics aspect, traditional depletion models assumed a linear relationship between catch as the result, and fishing effort and stock abundance as the causes of the catch. Therefore, it is common with these traditional depletion models to use the catch per unit of effort on the l.h.s of the equation and the abundance dynamics in the r.h.s. of the equation. Generalised depletion models allow for nonlinear dynamics for the effect of fishing effort and stock abundance on catch, and therefore fishing effort is not used as a standardising quantity but as a predictor on the r.h.s. of the equation. Perhaps more importantly, generalised depletion models allow for a nonlinear effect of stock abundance on the resulting catch, which allows considering phenomena such as hyper-stability [27].

With those introductory remarks, we can now define precisely the depletion model that we used to separately assess the the jumbo squid stock in Chilean EEZ waters on one hand and in international waters on the other hand. Let C be the expected total catch under the model and let t be a month in the time series. Let $E_{t,f}$ be the total fishing effort in month t. Then the model states that

$$
\begin{aligned}
C_t &= kE_t^{\alpha}N_t^{\beta} \\
C_t &= kE_t^{\alpha}e^{M/2}\left(N_0e^{-Mt} - e^{M/2}\left[\sum_{i=1}^{i=t-1} C_ie^{-M(t-i-1)}\right] + \sum_{j=1}^{j=Y} I_jR_je^{-M(t-\tau_j)}\right)^{\beta}
\end{aligned}
\tag{1}
$$

where:

- t is the time step (month),
- C is the unobserved, true catch in numbers,
- k is a proportionality constant, the scaling, that corresponds to the catch taken by a unit of effort and a unit of abundance, usually in the order of 10^{-4} to 10^{-8},
- E is the observed fishing effort,
- N is the latent stock abundance in numbers,
- α is a dimensionless modulator of effort as a predictor of catch, called the effort response,

- β is a dimensionless modulator of abundance as a predictor of catch, called the abundance response,
- M is the natural mortality rate with units of month^{-1},
- N_0 is the initial abundance, the abundance at month before the first month in the effort and catch time series (December 2012),
- Y is the number of years (nine for the Asian fleets, 11 for the Chilean fleets),
- i is an index that runs over previous time steps and up to the current time step (t),
- R are the magnitudes of annual pulses of recruitment of jumbo squid that grow to the size retained by the fishers,
- I is an indicator variable that evaluates to 0 before the recruitment pulse and to 1 during and after the recruitment pulse,
- 9 is the number of recruitment pulses, one for each year, happening at a specific month each year, with j being the counter that runs from 1 to 16, and
- τ is the specific month at which each recruitment pulse happens.

In the second line of Eq. 1, latent abundance available to the fleet is made explicit and expanded with Pope's equation (second sum inside parentheses) and the input of abundance (third sum inside parentheses) corresponding to the annual recruitment (R) to the fleet in year j ($j = 1, ..., 9$, 2012 to 2020). Parameters N_0 and M are the initial abundance (January 2012) and the average (across the whole period) monthly natural mortality rate, respectively. The variable I_j is an indicator that takes the value of 0 before the input of recruitment and 1 afterwards. Finally, parameters τ_j are the months in which recruitment happens in year j.

This model was applied to the data of the three Asian fleets pooled together taking advantage of the common effort metric (number of days) and the fact that the effort-catch relationship was similar in all three fleets (Fig. 2. The same reasoning was applied to pool together the data from the two Chilean fleets (Fig. 4). Moreover, considering the wide separation in the fishing grounds of the Asian and Chilean fleets ((Fig. 7), we fitted the above model to the Asian data and the Chilean data separately.

The model in Eq. 1 is the process model, the postulated mechanism linking the true catch C_t to effort and abundance, which is assumed to be fairly complete and exact, with negligible process error. The true catch time series however, are not observed. Instead, random time series $\chi_{f,t}$ are observed and its expected value is $C_{f,t}$. Thus the catch time series are random variables and the stock assessment model is completed with a statistical model where $\chi_{f,t}$ has a probability density, a specific parametric distribution. In this work, two distributions are be implemented to Asian and Chilean fleets, normal and lognormal, corresponding with additive or multiplicative hypotheses for the observations of catch. In implementing the normal and lognormal distributions for the fleet's catch data, we used two likelihood functions as alternatives, exact normal, excat lognormal, adjusted profile approximations to the normal, and adjusted profile approximations to the lognormal. The latter approximation have the following definitions:

$$l_p(\boldsymbol{\theta};\{\chi_t,E_t\}) = \begin{cases} \frac{T-2}{2} log\left(\sum_{i=1}^{T}(\chi_t - C_t)^2\right) & Normal \\ \frac{T-2}{2} log\left(\sum_{i=1}^{T}(log(\chi_t) - log(C_t))^2\right) & Lognormal \end{cases} \tag{2}$$

where l_p is the negative log-likelihood function, $\boldsymbol{\theta}$ is the vector of parameters, $\{\chi_t, E_t\}$ are the catch and effort data, C_t is the predicted catch according to the model in Eq. 1, and T is the total number of months ($T = 108$ with nine years of data). These negative log-likelihood functions are minimised numerically as a function of $\boldsymbol{\theta}$ to estimate maximum likelihood parameter values and their covariance matrix. The $108+ \times 108+$ covariance matrix contains the asymptotic standard errors of parameter estimates along its main diagonal and the covariances/correlations in the off diagonal triangles.
The model has 15 differentiable parameters for the Chilean fleets and 13 differentiable parameters for the Asian fleets. In addition to these differentiable parameters, the model has 20 years $\times$ 6 fleets $=$ 140 τ non-differentiable parameters corresponding to the month of recruitment in each year. They can be estimated by maximum likelihood by fitting models with alternative τ for each year and selecting the fit that maximises the likelihood. In this work the τ parameters were initially evaluated using the non-parametric catch spike statistics [28],

$$Spike_t = 10\left(\frac{\chi_t}{max(\chi_t)} - \frac{E_t}{max(E_t)}\right) \tag{3}$$

where χ is the observed catch. It highlights time steps with excessively high catch for the effort at that time step. Thus large positive spikes suggest recruitment pulses. See Fig. 3 in Roa-Ureta et al. [22] for a graphical demonstration of the use the spike statistic.

After examination of optimization results with this initial timing hypothesis, further hypotheses were evaluated by changing the months of recruitment for some years. The final best was selected as the one with the lowest Akaike Information Criterion (AIC) as well as better numerical, biological realism and statistical quality criteria. Firstly, all fits returning a numerical gradient higher than 1 were eliminated. This is a commonly employed criterion in stock assessment [34, 35, 36, 37]. Secondly, variants yielding unrealistic values of the natural mortality rate (i.e. less than 0.01 per month) given the known lifespan of the jumbo squid were also excluded. Thirdly, from the short list of model fits, the best fit was selected as the one with the lowest standard errors and with the histogram of correlation coefficients between parameter estimates more concentrated around zero. The histogram of correlation coefficients presents the distribution of pairwise correlations between parameter estimates. It is desirable that these correlations are as far away from 1 or -1 as possible because that means that each parameter was a necessary component of the model. Information theory model selection methods such as the Akaike Information Criterion (AIC) are also useful at this stage when comparing models run with the same likelihood or approximation to the likelihood.

Generalized depletion models were fitted using R package CatDyn [38]. All parameters were free parameters to be estimated, none of them was fixed at arbitrary values. CatDyn also estimates fishing mortality per month using a numerical resolution (R function *uniroot*) of the Baranov equation from estimates of abundance, natural mortality and (observed and estimated) catch per month. CatDyn depends on package optimx [39], which makes it simple to call several numerical optimization routines as alternatives to minimise the negative log-likelihood. The spg and the CG numerical routines were employed because these have yielded reliable results in previous applications [22, 40, 38].

2.3 Population dynamics models

Generalized depletion models estimate abundance at the start of the time series in the N_0 parameter. Abundance then drops and is reset to a higher value with every input of abundance due to recruitment, one for each year in the time series. Therefore, for each year, total abundance (initial abundance plus recruitment inputs) at all time steps (108 months) can be obtained by rolling back recruitment pulses from the month of recruitment and adding that to initial abundance decaying through natural mortality. Rolling back entails using the natural mortality rate estimate M with reversed sign. Knowing also the mean weight per month monthly abundance can be transformed into biomass, B_t. In addition, statistical uncertainty is propagated from initial abundance, natural mortality, and recruitment estimates and their covariance matrix, to each monthly total abundance using the delta method. This leads to time series of total monthly abundance and its standard error. Furthermore, total biomass at each time step B_t is estimated with its standard error using the total abundance estimate and its standard error and the mean weight in the catch per month and its standard error, with additional use of the delta method. The function CatDynBSD in CatDyn does this calculation to propagate statistical uncertainty in N_0, M, and mean weight, to B_t.

The estimated biomass time series and its standard error extends at monthly time steps over the complete time series. As it happens, it is often the case that a particular month produces the biomass estimate with the lowest standard error inside each year. We evaluate this month as the month at which the mean coefficient of variation (CV) of the biomass estimate is the lowest. The main purpose of using a particular month of biomass estimate from each year is to have an annual time step in the surplus production model. Having an annual time step is convenient because it is possible to use the landings from years prior to the year of the first biomass estimate with CatDyn, as additional data to fit the surplus production model. Selecting the month with the least average (across years) CV of the biomass estimate helps have more precise estimates of parameters in the surplus production model.

The South-East Pacific region is affected by the periodic occurrence of the El Niño Southern Oscillations (ENSO) leading to multi-annual periods of increased water temperature followed by multi-annual periods of colder or normal temperature [41]. These environmental oscillations may well affect the stock's population dynamics. We used NOAA's ENSO index [33] to define two environmental phases during our study period (Fig. 8). Then we defined four hypotheses of biomass dynamics during the study period (Fig. 8). The first hypothesis was the null hypothesis that the biomass dynamics was a conventional Pella-Tomlinson dynamics with constant parameters during the whole study period (2000 to

2020), i.e.:

$$B_y = B_{y-1} + rB_{y-1}\left(1 - \left(\frac{B_{y-1}}{K}\right)^{p-1}\right) - C_{y-1}, p > 1, y_1 \leq y \leq y_{end} \tag{4}$$

where

- r is the intrinsic population growth rate,
- p is the symmetry of the production function,
- K is the carrying capacity of the environment,
- B_y is the biomass estimated from generalized depletion models, and
- C_{y-1} is the total regional annual catch during the previous fishing season.

The three alternative hypotheses were that the biomass dynamics, i.e. the Pella-Tomlinson model, had time-varying parameters that followed the environmental cycle. The first alternative hypothesis had the intrinsic population growth rate r varying from r_1 to r_2 in 2014. The second alternative hypothesis established that both the carrying capacity of the environment K and the intrinsic population growth rate r varied from K_1 to K_2 and r_1 to r_2 in 2014. The third alternative hypothesis modelled all three parameters, K ,r and the symmetry of the production function, varied from K_1 to K_2, p_1 to p_2 and r_1 to r_2 in 2014.

Total regional annual biomass and its standard error from fitting generalized depletion models and the annual biomass predicted by fourteen variants of the Pella-Tomlinson model are linked through a hybrid (marginal-estimated) likelihood function,

$$\ell_{HL}(\boldsymbol{\theta}_{PT}|\{\hat{B}_y\}) \propto -\frac{1}{2}\sum_{2012}^{2020}\left(log(2\pi S^2_{\hat{B}_y}) + \frac{(\hat{B}_y - B_y)^2}{S^2_{\hat{B}_y}}\right) \tag{5}$$

where

- $\boldsymbol{\theta} = \{K, r, p\}$ is the vector of parameters of the Pella-Tomlinson model in Eq. 4. In all hypotheses it is assumed that the biomass in the first year in the landing time series, 2000, is equal to the carrying capacity of the environment (initial probes with the null hypothesis model and B_0 as additional parameter did not yield convergence in ADMB),
- $S^2_{\hat{B}_y}$ are the distinct numerical estimates of standard deviations of each annual biomass estimate from the fitted generalized depletion model (replacing the unknown distinct true standard deviations),
- $\hat{B}_y$ are the maximum likelihood estimates of annual biomass from the fitted generalized depletion model, and
- B_y are the true annual biomass according to Eq. 4

From the fit of Pella-Tomlinson model, several biological reference points were calculated depending on the prevailing dynamics of the stock. The reference points were the MSY,

$$MSY = rK(p-1)p^{-p/(p-1)} \tag{6}$$

the biomass at the MSY,

$$B_{MSY} = Kp^{1/(1-p)} \tag{7}$$

and the latent productivity,

$$\dot{P} = \gamma MSY \frac{B_y}{K}\left(1 - \left(\frac{B_y}{K}\right)^{p-1}\right), \gamma = \frac{p^{p/(p-1}}{p-1} \tag{8}$$

For each biological reference points, standard errors were computed using the delta method whenever possible.

With reference to the latent productivity [42], this is a biological reference point analogous to the MSY, but while MSY is a constant, the latent productivity varies with the biomass of the stock (compare Eq. 5 to Eq. 7). Thus the latent productivity is more relevant for stocks that tend to fluctuate because of environmental forces or because of their intrinsic population dynamics. For instance, in [19] we found that the stock under study was fluctuating because of a high value of the intrinsic population growth rate, r. In another case [22] we found that the stock was undergoing cyclic fluctuations due to an unstable equilibrium point in the spawners-recruitment relationship. Thus the MSY was not applicable in those cases and it was actually an excessive harvest rate. In the present case, if the stock was found to have a stationary equilibrium, MSY and B_{MSY} were computed as biological reference points, while if the stock was found to be fluctuating, the latent productivity was computed as the biological reference point. Both MSY and latent productivity can be used directly as sustainable limit harvest rates.

The analysis at this stage was programmed in ADMB [43] using ADMB-IDE 10.1 64 bits [44]. We created ADMB code for each of the four environmental influence hypotheses. Taking advantage of facilities of the ADMB system, parameter estimation was carried out by bounded or unbounded optimization, depending on the parameter and the model variant, and the sdreport function was used to produce annual biomass estimates with their standard errors.

3 Results

3.1 Generalized depletion models

The selected fit the depletion model to the Asian catch in numbers data and effort data was conducted with the adjusted profile normal likelihood and spg numerical method. The fit to data is shown in Fig. 9. The model does not fit the data very well probably due to using imputed mean weight data from literature instead of the actual mean weight in the catch of the Asian fleets. The model estimates a escapement biomass (at the last month, December 2020) of close to 7 million tonnes. Diagnostics plots show a good histogram on residuals, a widening spread over time, and systematic departures from the diagonal in q-q plots.

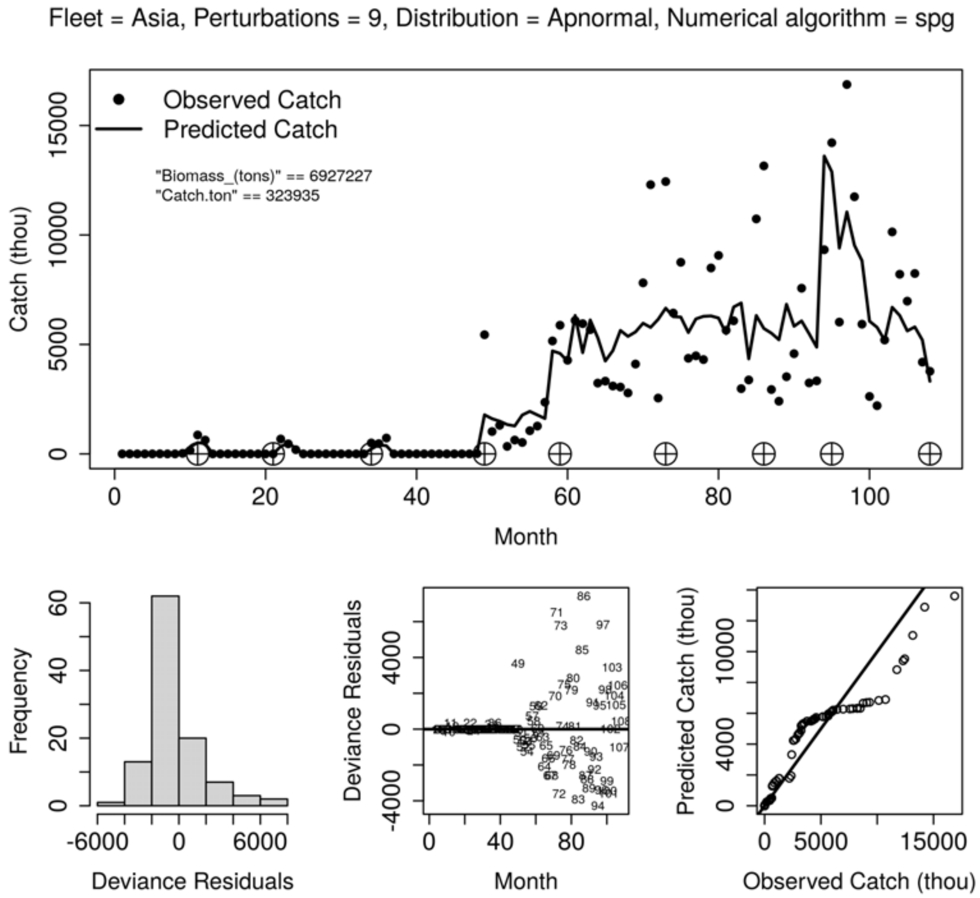

Figure 9: Fit of the depletion model to catch in numbers data from Asian fleets operating on the fishery for the jumbo squid in international waters of the SEP. Top panel: Model fit to data also indicating timing of recruitment inputs (target symbol), escapement biomass, and annual catch. Bottom panels, from left to right: histogram of residuals, residual cloud, and q-q plot.

The selected fit the depletion model to the Chilean catch in numbers data and effort data was conducted with the adjusted profile normal likelihood and spg numerical method. The fit to data is shown in Fig. 10. The model fits the data very well, closely following the ups and downs in the catch time series. The model estimates a escapement biomass (at the last month, December 2021) of close to 260 thousand tonnes. Diagnostics plots show a good histogram on residuals, constant spread over time, and no systematic departures from the diagonal in q-q plots. Just two months of data appear to have catches that are far higher than predicted by the model.

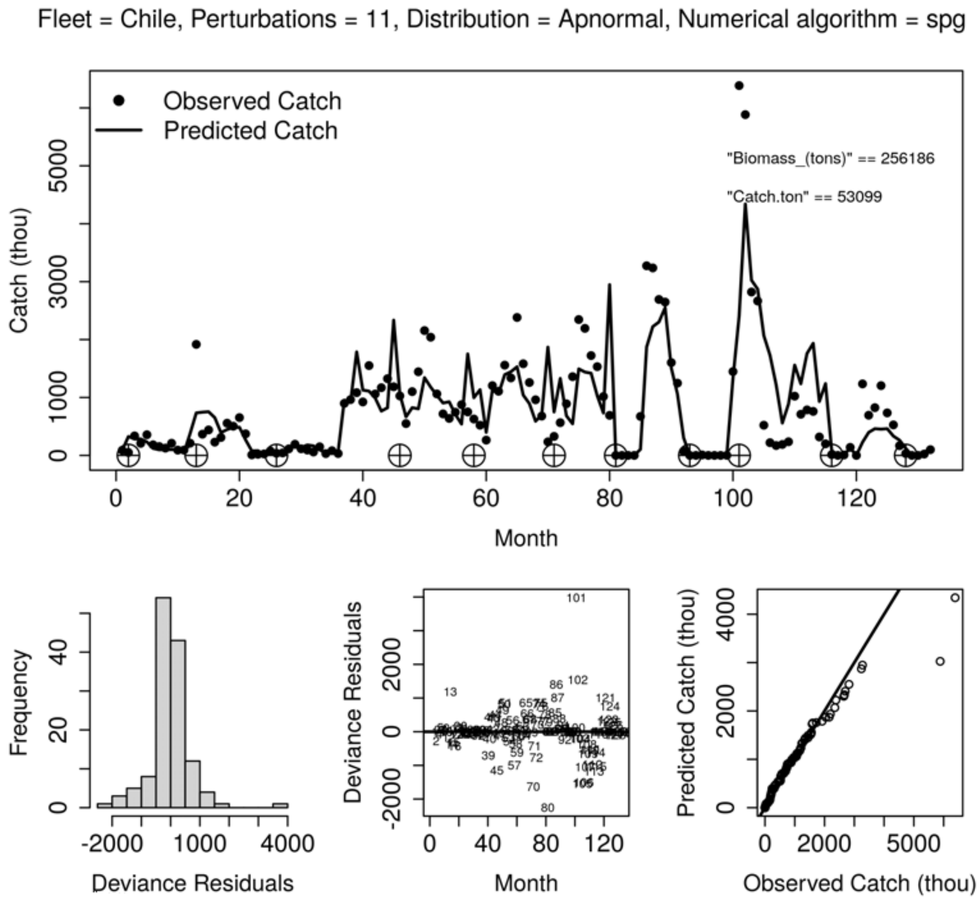

Figure 10: Fit of the depletion model to catch in numbers data from Chilean fleets operating on the fishery for the jumbo squid in EEZ Chilean waters of the SEP. Top panel: Model fit to data also indicating timing of recruitment inputs (target symbol), escapement biomass, and annual catch. Bottom panels, from left to right: histogram of residuals, residual cloud, and q-q plot.

Estimated parameters by the selected depletion model for the Asian fleets data and the Chilean fleets data are shown in Table 1. In both models the estimated natural mortality rate was similar, amounting to 0.66 and 0.82 in annualised value for the Asian and Chilean fishing grounds, respectively. These natural mortality estimates are estimated with good precision. In the Asian fleets, annual recruitment estimates are usually in the low billions while in the Chilean fleets these are in the order of tens to hundreds millions. In both fleets the gear is saturable ($\alpha < 1$) and there is little hyper-stability or hyper-depletion ($\beta \approx 1$). The estimates are mostly imprecise in the Asian fleets while there are many reasonably precise estimates of recruitment to the Chilean fleets.

Table 1: Directly estimated parameters from the best generalised depletion models for the Asian and Chilean fleets. Absent CVs mean that the optimizer did not return standard errors for the corresponding parameter estimates.

Fleet	**Parameter**	**Timing**	**Estimate**	**CV** (%)
Asian fleets	M (1/m)		0.05535	11.0
	N_0 (thousand)		2,074,035	
	Recruitment (thousand) 2012	2012-11	4,016,429	
	Recruitment (thousand) 2013	2013-9	2,048,176	643.5
	Recruitment (thousand) 2014	2014-10	1,297,113	529.7
	Recruitment (thousand) 2015	2015-12	467,229	496.5
	Recruitment (thousand) 2016	2016-11	2,593,032	
	Recruitment (thousand) 2017	2017-12	1,274,683	54.5
	Recruitment (thousand) 2018	2019-2	591,738	88.5
	Recruitment (thousand) 2019	2019-11	1,451,828	79.6
	Recruitment (thousand) 2020	2020-12	39,443	505.2
	k (1/days)		0.000002112	
	α		0.8658	33.2
	β		0.9875	
Chilean fleets	M (1/m)		0.06830	16.8
	N_0 (thousand)		87,186	262.0
	Recruitment (thousand) 2011	2011-2	98,948	241.4
	Recruitment (thousand) 2012	2012-1	471,322	33.8
	Recruitment (thousand) 2013	2013-1	36,756	225.5
	Recruitment (thousand) 2014	2014-10	101,360	23.6
	Recruitment (thousand) 2015	2015-9	94,458	22.4
	Recruitment (thousand) 2016	2016-11	83,905	25.4
	Recruitment (thousand) 2017	2017-9	142,066	19.4
	Recruitment (thousand) 2018	2018-9	26,742	333.3
	Recruitment (thousand) 2019	2019-4	266,073	23.0
	Recruitment (thousand) 2020	2020-7	8,394	306.4
	Recruitment (thousand) 2021	2021-7	22,375	341.7
	k (1/days)		0.0000005681	43.0
	α		0.8073	14.4
	β		1.2829	7.3

Putting together biomass estimates from depletion models for the Asian and Chilean fishing grounds and biomass estimates from the standard surplus production model with data published in Peruvian official reports, it is clear that there is a downward trend in biomass in international areas and the Peruvian EEZ while the it seems to be constant in Chilean EEZ waters (Fig. 11). The total biomass time series and the regional landings time series were used to fit constant- and varying-parameters surplus production models of the Pella-Tomlinson type.

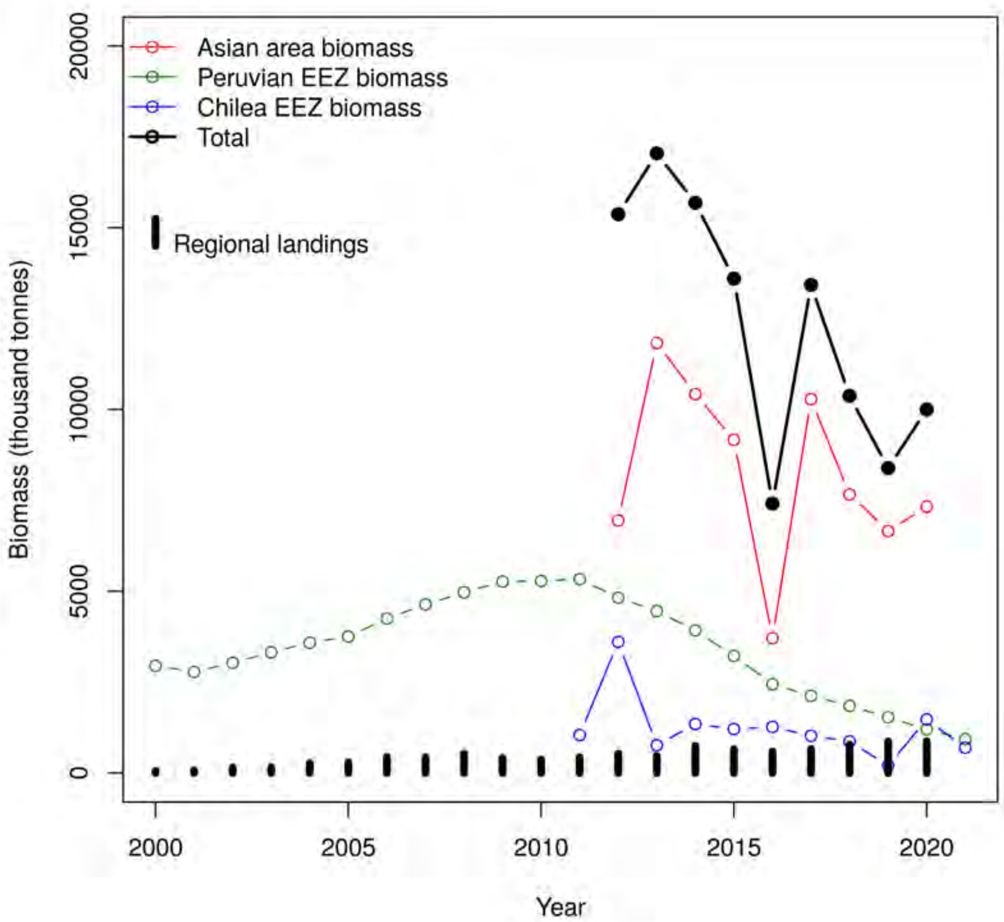

Figure 11: Estimated biomass time series from the three areas studied in this work and total regional landings.

3.2 Population dynamics models

The fitted Pella-Tomlinson dynamics from the best hypothesis as well as biomass estimates as input observations and the time series of total annual catch, are shown in Fig. 12. The best hypothesis for Pella-Tomlinson dynamics included time-varying estimates in all three parameters, K, p and r. All four hypotheses were yielded models with the maximum absolute gradients less than 1, all converged successfully within given bounds for parameters, and were all tied with respect to the AIC, but the time-varying hypothesis with changes in all three parameters had better correlations between estimates (clustered around 0) and better CVs of estimates. Biomass estimates from best depletion model plus the Peruvian biomass and the best Pella-Tomlinson surplus production biomass show good agreement, although biomass predictions from the Pella-Tomlinson model (directly from ADMB) are estimated with poor statistical precision. The Pella-Tomlinson model shows that the stock was fairly stable over most of the initial decade, close to the 15 million tonnes mark, but it started to fluctuate around this mean towards the end of the cold environmental period. At the start of the second, warmer environmental period, the stock underwent much wider fluctuations centred around the mark of 10 million tonnes. During the whole time series, regional landings remained far below stock biomass.

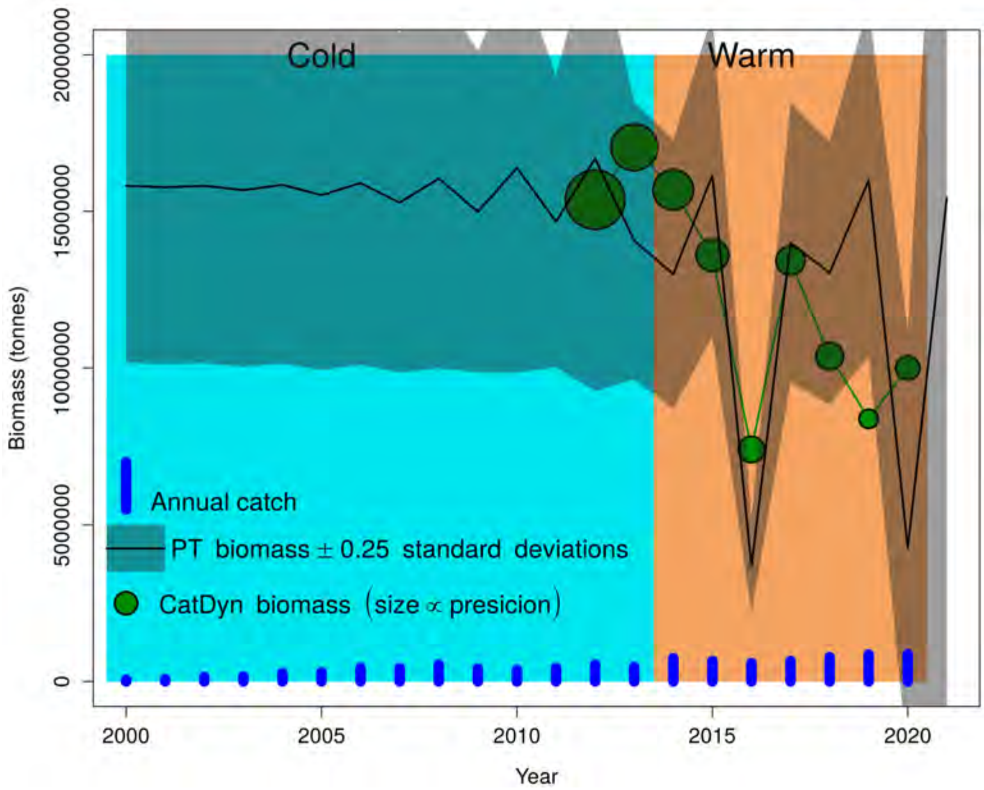

Figure 12: March stock biomass estimated by the best generalized depletion model CatDyn R package, best hypothesis for Pella-Tomlinson model of population dynamics, and total regional catch by Asian, Peruvian and Chilean fleets operating in the jumbo squid fishery in the South-Eastern Pacific.

Some parameters of the Pella-Tomlinson model were fitted with reasonable precision (Table 2) although most have CVs larger than 100%. The carrying capacity decreases from the cold to the worm period but the major change is observed in the intrinsic rate of growth, which increases 62% from the cold to the warm period. The stock is far more productive during the warm period, with total latent productivity $\dot{P}$ more than doubling with respect to cold period. Catches in the warm period are also on average more than twice the the average catches during the cold period. In both periods, catches are about half of the total latent productivity, indicating that the exploitation has been conducted well within sustainable levels during the whole time series. Nevertheless, the facts that the stock fluctuates widely during the warm period and that it started to fluctuate earlier, during the second half of the cold period, calls for precaution due to the possibility that larger catches may induce even wider fluctuations that may lead to one year to having very low biomass.

Table 2: Directly estimated parameters from the best Pella-Tomlinson model and derived biological reference points (MSY, B_{MSY}, and $\dot{P}$) for the jumbo squid in the South-East Pacific according to parameterization in Eqs. 4, 6-8, likelihood model in Eq. 5. $\dot{P}$ the annually averaged total latent productivity under the cold and warm environmental regimes, respectively (see Eq. 5).

Regime	**Parameter**	**Estimate**	**Standard error**	**CV (%)**
Cold	K (tonnes)	15,821,000	22,621,000	143.0
	p	2.0018	0.96830	48.4
	r (1/yr)	2.2868	1.6862	69.5
	MSY (tonnes)	9,056,145	16,272,567	197.7
	B_{MSY} (tonnes)	7,913,249	11,996,023	151.6
	$\dot{P}$ (tonnes)	751,272		
	Mean annual landings (tonnes)	327,242	164,450	50.2
Warm	K tonnes	13,930,000	17,206,000	125.8
	p	2.2187	1.6862	76.0
	r	3.6950	3.7481	101.4
	MSY (tonnes)	14,701,912	36,131,860	245.8
	B_{MSY} (tonnes)	7,243,711	9,421,556	130.1
	$\dot{P}$ (tonnes)	1,824,674		
	Mean annual landings (tonnes)	737,729	107,842	14.7

It is noted that due to large statistical uncertainty in the biomass times series (Fig. 12) it was not possible to calculate standard error of total latent productivity $\dot{P}$ using the delta method.

4 Discussion

The stock assessment model developed and implemented in this work shows that it is feasible to understand the population dynamics of the jumbo squid in the Southern Eastern Pacific Ocean (SEP) and derive management-useful biological references points at the regional level with monthly total catch, fishing effort and samples of the mean weight of squids in the catch. However, it needs improvements in the data used to asses the stock.

In particular, it is most important to have observed biological sampling data from the Asian fleets. In this work we used data published in academic works [29, 3] but that is a blunt tool to replace missing data. Fig. 9 shows that model predicted catch could not follow the ups and downs of the catch data which most likely is a consequence of poor transformation of catch in weight to catch in numbers. Works like those of Liu et al. [29] show that the data exist and therefore could be contributed to improve the stock assessment using the methodology presented here. A collaborative effort with Chinese experts in this endeavour would be welcome, especially when noting the Chinese fleet is the largest and the one covering the larger part of stock distribution (Fig. 7).

Further improvement of the database for stock assessment could be contributed by having Peruvian catch, effort and mean weight data at monthly time steps, at least during the period of the Asian database, 2012 onward. Peruvian data would allow fitting a multi-annual generalised depletion model to the Peruvian EEZ fishing grounds as done for the Chilean and Asian fishing grounds. The current estimates of biomass from application of standard surplus production models fitted to CPUE data appear overly smoothed probably due to the use of the annual time step (Fig. 11. Finer time resolution of stock biomass from depletion models could thus further contribute to improve statistical precision at the level of the surplus production model. Collaboration with Peruvian experts may lead to achievement of this aim.

Completing the Ecuadorian database with respect to 2019 would also help providing the methodology with more data and assess the part of the stock inside Ecuadorian EEZ. These data unfortunately appears not to be available prior to 2018. Nevertheless, the methodology can be adapted to accept a time series of Ecuadorian fishing starting in January 2018 and extending to the present. Collaboration with Ecuadorian experts is already underway.

In the South-East Pacific, environmentally driven transitions in population dynamics, connected to well know cycles in oceanographic and atmospheric processes in the whole Equatorial Pacific, have a significant impact on sustainable harvest rates for fishers operating on the jumbo squid stock. Normal or cold periods have lower sustainable harvest rates than warm, ENSO periods, and fishers have correspondingly lower catches when sustainable harvest rates are lower. This happens without knowledge of sustainable harvest rates in cold versus warm periods of the environmental cycle. This coincidence implies that there could be natural processes that force less fishing yield when productivity is lower in this fishery.

During warm, ENSO periods, the stock experiences wider fluctuations in abundance compared with cold, normal periods of the environmental cycle. These periods of warmer waters and wider fluctuations provide a window of opportunity for better determination of the population dynamics by the stock assessment model. This is represented by narrower bands of statistical error during a short period of wide fluctuations (2015 to 2017) in the biomass trajectory of the stock (Fig. 12). The mathematical reason for wider fluctuations during warm water periods is that r is 62% higher. Nevertheless, the stock started to fluctuate during the second half of the cold period, suggesting that there also drivers connected to fishing removals. It is plausible that the environmental cycle drives an intrinsic population cycle into wider or narrower fluctuations and that this process overlaps with fluctuations started by fishing removals.

5 Conclusions

1. A stock assessment database of monthly catch, effort and mean weight data for the jumbo squid in the South-East Pacific (Peru, Chile and international waters) with the activity of five fleets, spanning 2011 to 2021, has been compiled and curated.

2. A statistical stock assessment methodology and its code in the R language of statistical programming and in ADMB, as well as binary storage of the database and programming objects, is now available for updated assessment of the jumbo squid in the South-East Pacific as more data are collected.

3. The stock assessment methodology was applied to the jumbo squid at the regional level in South-East Pacific resulting in biologically realistic estimates of population dynamics some of them with good statistical precision.

4. Analysis of the NOAA indicator of ENSO determined the existence of an environmental cycle with two periods, starting with a cold, normal period (2000 to 2013), and ending in a warm period (2014-2020).

5. The biomass dynamics of the stock in the region is driven by environmental cycles connected to the ENSO, leading to changes in the carrying capacity of the environment, the symmetry of the production function, and the intrinsic rate of population growth.

6. During warm, ENSO years the stock has higher sustainable harvest rates and wider fluctuations than during normal, cold water periods.

7. Actual harvest rates during warm, ENSO years as well during cold, normal periods have been well below the sustainable harvest rates of each period.

8. Results from this stock assessment methodology can be improved substantially by a collaborative effort with Chinese, Peruvian and Ecuadorian experts to compile a more complete database of monthly catch, fishing effort and mean weight.

9. Results from depletion models (high escapement biomass) and surplus production model (catches well below limit sustainable harvest rates) indicate that the stock is not overfished and not undergoing over-fishing.

List of Figures

List of Tables

References

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