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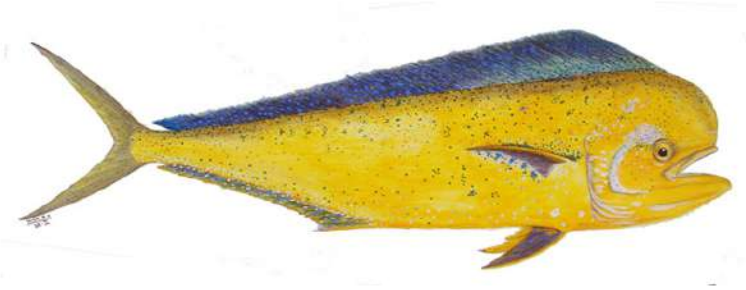

Stock Assessment of the dolphinfish (*Coryphaena hippurus)*) in the South-East Pacific Ocean

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Contents

1 Introduction

The dolphinfish is a large epipelagic and migratory species from tropical and subtropical oceans that has been fished in all regions where it is found since ancient times [1]. The species is captured in large volumes (thousand tonnes) in the Western Indian Ocean (Iran and Pakistan), North-West Pacific (Taiwan), Western Central Pacific (Indonesia), Western Mediterranean (Italy, Tunisia, Spain and Malta) and the South-East Pacific (Peru and Ecuador) [2]. It is also captured in the Caribbean [3] and Florida and North Carolina, U.S.A [4]. The largest landings occur in the South-East Pacific and in particular the Peruvian fishery is the largest dolphinfish fishery in the world [2]. In the Exclusive Economic Zones (EEZ) of both Peru (815,915 km^2) and Ecuador (1,077,231 km^2, including the Galapagos archipelago) (Fig. 1) the dolphinfish is an important fishery resource captured by local artisanal fleets using drifting longlines.

Although the species sustains large total landings worldwide, well exceeding 100 thousand tonnes in the last decade (Fig. 2, top panel), the stock assessment of local stocks remains difficult due to scarcity of data and fast population dynamics. Nevertheless, several authors have attempted various stock assessment methods in their areas of operation. Benjamin and Kurup [5] applied yield per recruit and virtual population formulas to the stock fished off the South-West coast of India to conclude that the stock is fished within sustainable levels. Baset *et. al.* [6] applied non-equilibrium surplus production models to the dolphinfish catch records and (apparently un-standardized) annual CPUE indices of abundance from the Pakistan fishery using the CEDA stock assessment package [7]. This method depends on an assumption of depletion degree (0 to 90%) at the start of the time series and in Baset *et. al.* application, results varied widely depending on the value assumed (from MSY equal to a few thousands tonnes at low starting depletion degree values to a few million tonnes at high starting depletion degree values). Nevertheless, the authors concluded that the stock was being overfished due to catches larger than the most reasonable MSY estimates. Aires-da-Silva *et. al.* [8] conducted an exploratory stock assessment of the stock fished in the South-East Pacific, namely within the Peruvian and Ecuadorian EEZs (Fig. 1), using a length-structured model with monthly time steps in the Stock Synthesis package [9]. Although this assessment was technically more solid than the assessments cited above and it could be considered as data-rich and conventional, it included several parameters fixed at arbitrary values chosen by the analysts, such as the natural mortality rate, the steepness of the stock-recruitment relationship, and other parameters that resulted in giving more weight to specific pieces of data. The authors conclude that recent catches (up to June 2015) were close to the estimated MSY but that the fishing mortality that yields the MSY is undefined due to a flat yield-per-recruit curve. Finally, in the Mediterranean Sea the Food and Agriculture Organization of the United Nations (FAO) has been working on the assessment and management of the dolphinfish stock that migrates into the Mediterranean every summer and is fished there by artisanal fleets from several countries. In 2019 the working group assigned with the assessment of the stock recommended the implementation of generalized depletion models [10] and published a substantial review of dolphinfish biology and its fisheries [11]. Subsequently, the working group developed a customized version of generalized depletion models [12, 13, 14, 15, 16, 17] in software CatDyn [18] and applied it to the data from five fleets operating in the Western Mediterranean Sea [19]. This was reported as the first stock assessment that succeeded in yielding management-useful results. It showed that the stock was being fished in sustainable manner in the region.

Figure 1: Map of Peruvian and Ecuadorian EEZs where the fishery is conducted.

The dolphinfish Peruvian and Ecuadorian fisheries are clearly the largest dolphinfish fisheries worldwide, accounting for nearly 50% of worldwide dolphinfish catches since 2013 (Fig. 2, top panel). They have been described as data poor fisheries and the stock dynamics as highly productive, variable and fast, making the stock assessment by conventional methods (i.e. methods based on population dynamics and the biological composition of the stock) difficult to apply [20]. In this work, we have adapted the generalized depletion model built for the assessment of the stock in the Mediterranean Sea to the situation of the fishery in the South-East Pacific, namely Peruvian and Ecuadorian EEZs. Results of the four-fleets generalized depletion model are further used in a hierarchical inference statistical framework to fit a non-equilibrium surplus production model of the Pella-Tomlinson type. The approach is described in schematic fashion in Fig. 2 of Roa-Ureta et al. [16]. We present results useful for management in the form of instantaneous and aggregate exploitation rates, biomass levels that support sustainable exploitation, and catch rates that take into account the productive capacity of the stock.

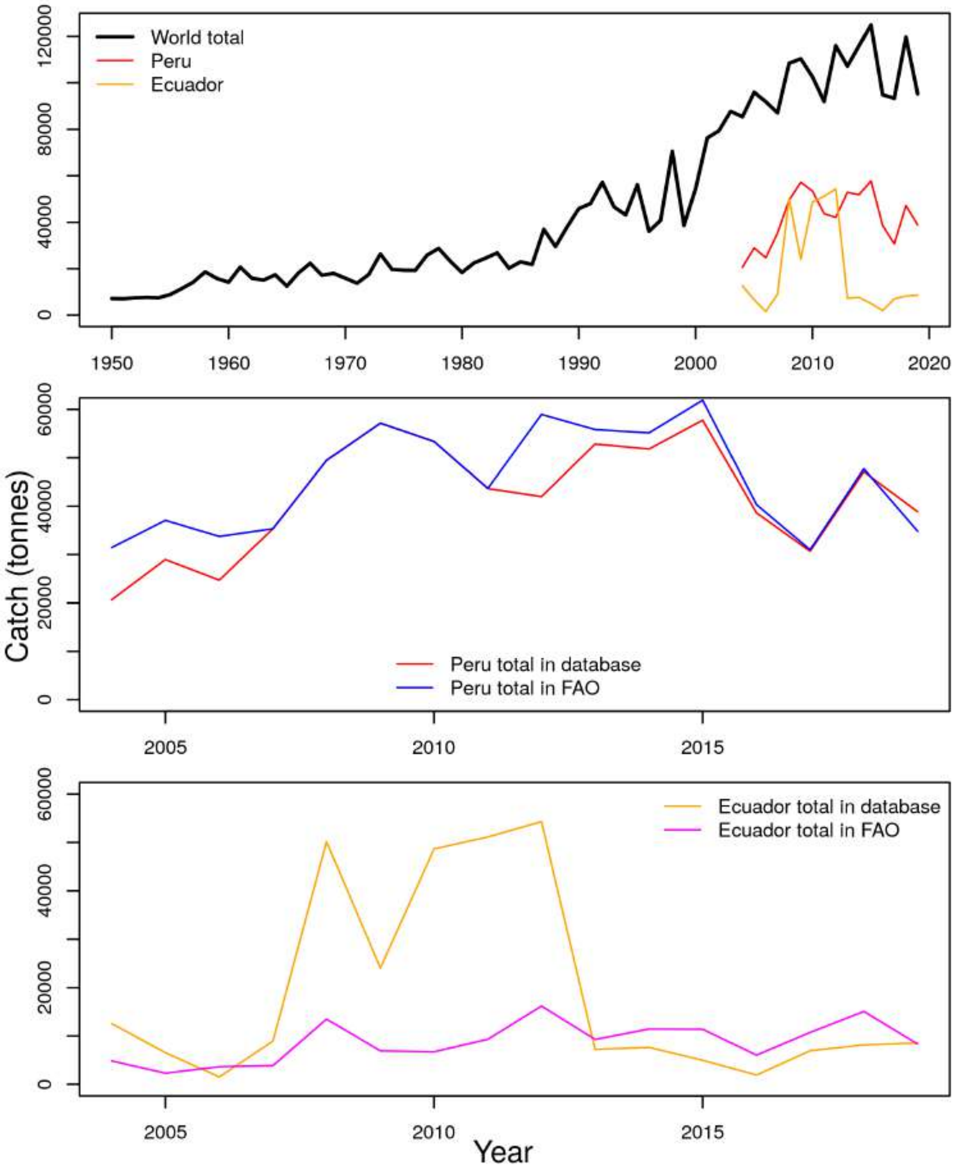

Figure 2: World and country landings and contrast between catch data in the stock assessment database and in FAO databases [21] for the two countries.

2 Materials and Methods

The general approach to the stock assessment of the dolphinfish stock in the South-East Pacific (Peruvian and Ecuadorian EEZs) consists of (1) developing and curating a database of monthly total catch, monthly total effort, and sampled mean monthly weight from four fleets (two artisanal fleets in each country) for the period of January 2004 to December 2019, (2) fitting several variants of generalized depletion models and selection of the best variants in terms of numerical, statistical and biological criteria, and (3) use some of the output from the best generalized depletion model to fit a surplus production model. Steps (2) and (3) yield several management-useful quantities that constitute potential biological reference points (BRPs).

2.1 Data

The database described in this subsection was compiled as a spreadsheet and then it was imported to the R system of statistical programming [22, 23], where it has been stored as a binary repository.

The data consisted of monthly total catch, monthly total effort, and sampled mean monthly weight or sample mean length from the Peruvian artisanal longline fleet, which operates in coastal and oceanic waters in the Peruvian EEZ, the Peruvian fibreglass boats fleet that operates in coastal waters in the Peruvian EEZ, the Ecuadorian artisanal fleet operating in coastal and oceanic waters in the Ecuadorian EEZ, and the Ecuadorian fibreglass boats fleet that operates in coastal waters in the Ecuadorian EEZ. The Peruvian part of the database contained sampled mean weight in the catch that could not be split between the artisanal and fibreglass fleets so it was considered as valid for both Peruvian fleets. The Ecuadorian part of the database contained sampled mean length in the catch that also could not be split between the artisanal and fibreglass fleets so it was considered as valid for both Ecuadorian fleets. The period covered was January 2004 to December 2019. When aggregated to the annual time step and across both types of fleet per country, the Peruvian catch data shows substantial agreement with the data reported to FAO (Fig. 2, middle panel) while the Ecuadorian catch data shows agreement with that reported to FAO beytween 2004 and 2007 and between 2013 and 2019, with substantial differences between 2008 and 2012 (Fig. 2, bottom panel). At this point we considered the new database compiled for Ecuador as more accurate than the totals reported to FAO, thus the stock assessment was conducted using the newly compiled database, which included a large increase in Ecuadorian catches between 2008 and 2012.

The original database compiled for stock assessment had missing data. The pattern of missing data is shown in Fig. 3. Over 60% of mean weight data from Peruvian fleets is missing, followed by fishing effort by the Ecuadorian fibreglass fleet at over 40%, and the last significant amount of missing data being the sample mean length data of Ecuadorian fleets (Fig. 3, left panel). Most months (60) are missing mean weight in the catch of the Peruvian fleets and fishing effort by the Ecuadorian fibreglass fleet, with another large number (34) just missing mean length in the catch of Ecuadorian fleets (Fig. 3, right panel).

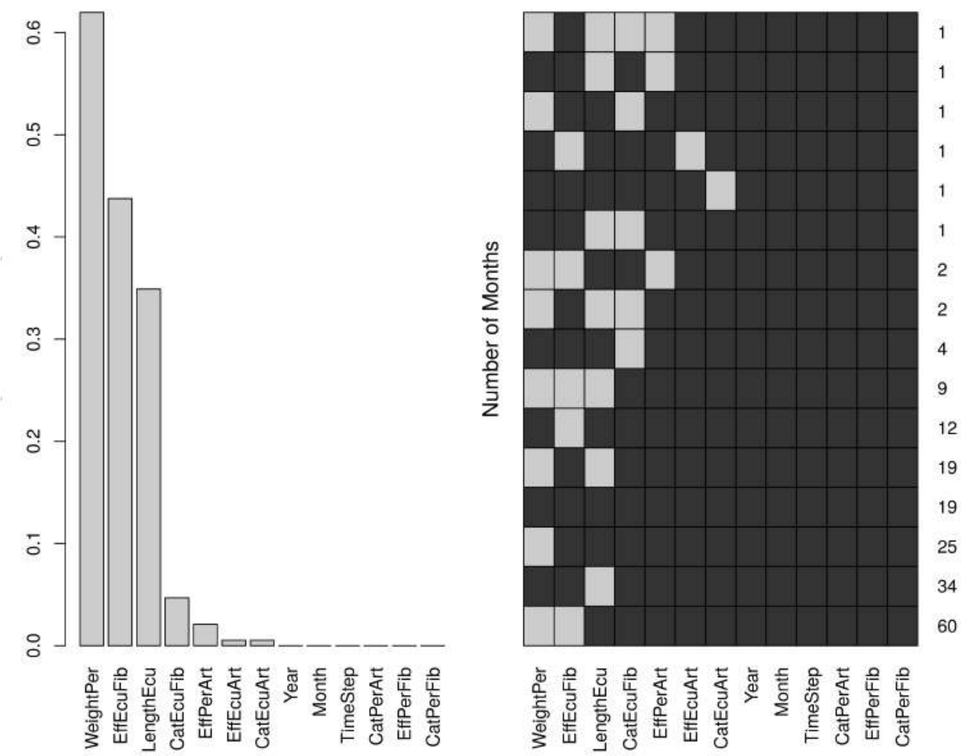

Figure 3: Pattern of missing data in the original database compiled for stock assessment of the stock of dolphinfish in the South-Eastern Pacific (Peru and Ecuador). The left panel is a histogram of months with missing data per variable. The right panel is the number of months missing data at particular combinations of the variables. The variables are *WeightPer*: mean weight in Peruvian catches; *EffEcuFib*: total fishing effort in the Ecuadorian fibreglass fleet; *LengthEcu*: mean length in Ecuadorian catches; *CatEcuFib*: total catch in the Ecuadorian fibreglass fleet; *EffPerArt*: total fishing effort in the Peruvian artisanal fleet; *EffEcuArt*: total fishing effort in the Ecuadorian artisanal fleet; *CatEcuArt*: total catch in the Ecuadorian artisanal fleet; *CatPerArt*: total catch in the Peruvian artisanal fleet; *EffPerFib*: total fishing effort in the Peruvian fibreglass fleet; and *CatPerFib*: total catch in the Peruvian fibreglass fleet.

To replace all missing data with realistic imputed values, a standard statistical methodology for the imputation of indispensable missing data was implemented: predictive mean matching in R package mice [24]. This method consists of the following steps

- Carry out multiple linear regressions on the available data to predict the missing data. We had five completely observed variables (year, month, total catch of the Peruvian artisanal fleet, total effort of the Ecuadorian fibreglass fleet, and total catch of the Peruvian fibreglass fleet) and three nearly completely observed variables (total catch of the Ecuadorian artisanal fleet, total fishing effort of the Ecuadorian artisanal fleet, total fishing effort of the Peruvian artisanal fleet), so predictions are expected to be accurate. This produced slope estimates and their covariance matrix.

- Random sample slope values from the multivariate normal distribution created by slope estimates and their covariance matrix. By including the covariance matrix this step produces natural variability so predictions of missing data would look more realistic.

- Use the randomized slope values and observed data to predict the whole set of data, including in months in which true values were observed and were missing.

- For missing data, find the set of observed data that most closely resembles the same data in the missing effort months.

- Take one random value for each predicted datum from the set of predicted data that belongs with the observed data that most closely resembles the current missing data.

In this manner we assembled a complete database for stock assessment. Finally, mean length data in the catch of Ecuadorian fleets was used to calculate mean weight in the catch of those fleets. For this we used the length-weight relationship in Zúñiga-Flores [25], determined from dolphinfish samples of fork length and weight taken in Baja California, Mexico. The resulting effort and catch data is shown in Fig. 4. The best effort-catch relationship is observed in the Peruvian fibreglass fleet, followed by Peruvian artisanal fleet. Ecuadorian data show over-dispersion (fibreglass) and weak determination of catch from effort for a wide range of effort (artisanal).

Generalized depletion models predict the catch by time step in numbers, not in weight. Therefore the monthly catch recorded in weight in the database needed to be transformed to numbers by using the the time series of mean weight. The complete mean weight time series is shown in Fig. 5. There is ample intra-annual variability in both time series, as expected given the very fast growth rate that characterizes the species [11]. Ecuadorian fleets seem to catch larger fish than Peruvian fleets.

2.2 Generalized depletion models

The stock assessment methodology employed here has been described in several recent scientific articles [12, 26, 13, 27, 14, 15, 16, 17, 18, 28, 29]. The model developed for this case is an extension of multi-annual generalized depletion models [13, 16, 29]. These models run at monthly time steps and analyze the data from several annual fishing season simultaneously. The models contain parameters for initial abundance, the average natural mortality rate over the period of years covered by the time series of data, the magnitude of annual recruitment pulses to each fleet (i.e. there is a total number of number of years $\times$ number of fleets, $16 \times 4 = 64$ recruitment parameters) and three fishing operational parameters that are fleet-specific (i.e. $3 \times 4 = 12$ fishing operational parameters). These models are fully mechanistic models in which all parameters are estimated freely, not fixing any parameter at arbitrary values. The generalized depletion model specific to this case has 78 parameters to estimate and is of the form:

$$
\begin{aligned}
C_t &= k_1 E_{1,t}^{\alpha_1} N_t^{\beta_1} + k_2 E_{2,t}^{\alpha_2} N_t^{\beta_2} + k_3 E_{3,t}^{\alpha_3} N_t^{\beta_3} + k_4 E_{4,t}^{\alpha_4} N_t^{\beta_4} \\
C_t &= k_1 E_{1,t}^{\alpha_1} e^{M/2} \left(N_0 e^{-Mt} - e^{M/2} \left[\sum_{i=1}^{i=t-1} C_{1,i} e^{-M(t-i-1)} \right] + \sum_{j=1}^{j=16} I_{1,j} R_{1,j} e^{-M(t-\tau_{1,j})} \right)^{\beta_1} + \\
&\quad k_2 E_{2,t}^{\alpha_2} e^{M/2} \left(N_0 e^{-Mt} - e^{M/2} \left[\sum_{i=1}^{i=t-1} C_{2,i} e^{-M(t-i-1)} \right] + \sum_{j=1}^{j=16} I_{2,j} R_{2,j} e^{-M(t-\tau_{2,j})} \right)^{\beta_2} + \\
&\quad k_3 E_{3,t}^{\alpha_3} e^{M/2} \left(N_0 e^{-Mt} - e^{M/2} \left[\sum_{i=1}^{i=t-1} C_{3,i} e^{-M(t-i-1)} \right] + \sum_{j=1}^{j=16} I_{3,j} R_{3,j} e^{-M(t-\tau_{3,j})} \right)^{\beta_3} + \\
&\quad k_4 E_{4,t}^{\alpha_4} e^{M/2} \left(N_0 e^{-Mt} - e^{M/2} \left[\sum_{i=1}^{i=t-1} C_{4,i} e^{-M(t-i-1)} \right] + \sum_{j=1}^{j=16} I_{4,j} R_{4,j} e^{-M(t-\tau_{4,j})} \right)^{\beta_4}
\end{aligned}
\tag{1}
$$

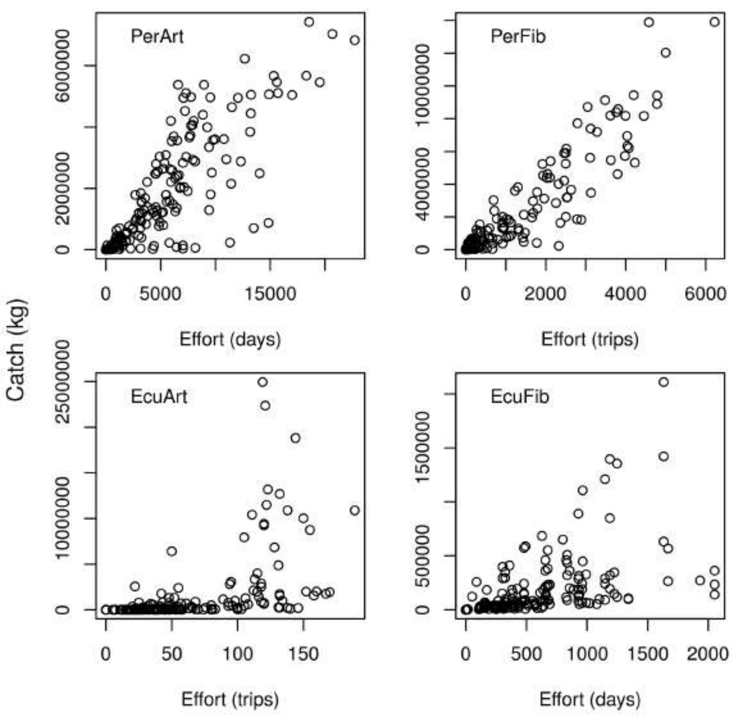

Figure 4: Effort and catch data in four fleets operating in the South-East Pacific (Peru and Ecuador). PerArt: Peruvian artisanal; PerFib: Peruvian fibreglass; EcuArt: Ecuadorian artisanal; EcuFib: Ecuadorian fibreglass.

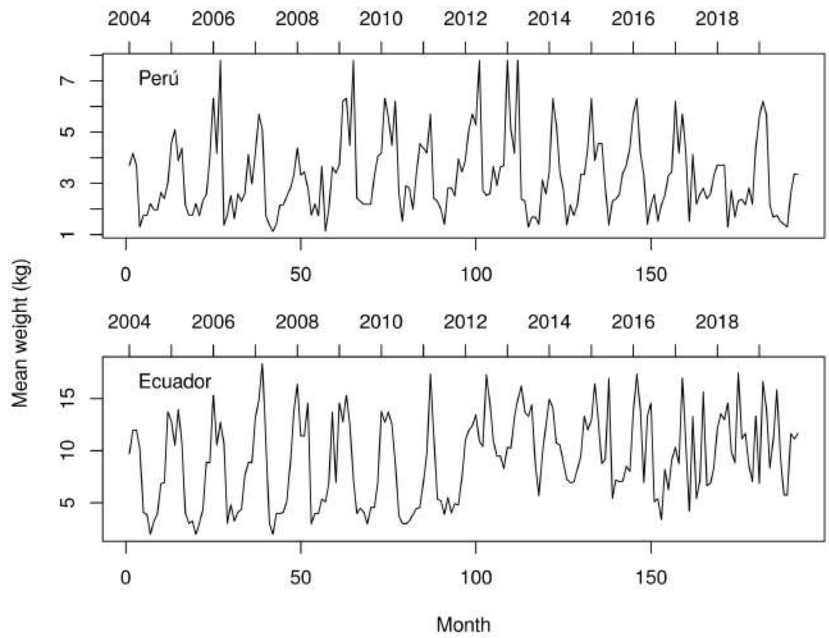

Figure 5: Mean weight time series used to transform catch in weight to catch in numbers.

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 in hours,
- 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},
- m equals $e^{M/2}$,
- N_0 is the initial abundance, the abundance at month before the first month in the effort and catch time series (December 2014),

- 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 dolphinfish that grow to the size retained by the fishers to each of the fleets,
- I is an indicator variables that evaluates to 0 before the recruitment pulse and to 1 during and after the recruitment pulse,
- 16 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.

Parameters M, N_0, and the 64 recruitment magnitudes are stock abundance parameters while k, α and β are fishing operational parameters. The conceptual basis of this model is presented in the first line of Eq. 1. The true catch at each month C is the product of the fishing effort E expended that month and the latent stock abundance that month, and this product is scaled by the scaling k. The model allows for zero catches in some months either because there was zero effort or there was zero abundance. The model is a mechanistic model because it ascertains a specific cause-effect: effort and abundance are necessary causes and the catch is the effect. In the second line of Eq. 1 the model is completed by using Pope's recursive expansion plus the effect of recruitment pulses to fully specify the mathematical form of C_t.

Parameters α and β are power modulators of the effect of both predictors on the true catch that enable discovery of nonlinear effects. Specifically, the effort response α modulates the continuum of effort saturation ($\alpha < 1$) $\leftrightarrow$ proportionality ($\alpha \approx 1$) $\leftrightarrow$ synergy ($\alpha > 1$) and the abundance response β modulates the continuum of abundance hyperstability ($\beta < 1$) $\leftrightarrow$ proportionality ($\beta \approx 1$) $\leftrightarrow$ hyperdepletion ($\beta > 1$). Effort saturation occurs when a fishing gear becomes full quickly so any additional unit of effort does not produce a proportional increase in catch, while the opposite effect, effort synergy occurs when additional units of effort produce more additional catch than expected under proportionality. Abundance hyperstability happens when declining stock abundance is not reflected in less catch, while abundance hyperdepletion happens when the catch decreases faster than the decline in the stock. Effort saturation may happen when fishing gears are small, for instance a crab trap may not catch more crabs even though it stays longer time because it is full of crabs. Effort synergy happens when fishing gears work better when there are more of them, for instance traps that have baits, which when larger in number, create a greater area of attraction to the target stock. Hyperstability is common in fisheries that capture aggregations of fish since the catch may remain high even when aggregations are being depleted because the fish will aggregate again as the gear thins the aggregation making it possible for the fishers to continue having high catches as abundance decreases. Hyperdepletion happens when fishing gears scare the fish away so it seems from the fishers point of view that the stock is being depleted while the reality is that the stock is being dispersed.

In the model, total recruitment to the stock in any year is the sum of the recruitments to each fleet: $R_y = R_{1,y} + R_{2,y} + R_{3,y} + R_{4,y}$, where y is the year, and the concept behind this additivity is that each fleet 'sees' a part of the total recruitment.

Using the catch in numbers and effort time series for sufficiently long time series (i.e. when the number of time steps is several times the number of parameters) allows simultaneous estimation of N_0, M, k, the recruitment pulses R_j, α, and β. The timing τ_j of recruitment pulses are estimated by fitting models with varying configurations of τ_j and then selecting the configuration best supported by the data. These configurations are defined by a range of possible integer values for τ_j, that translate into a range of time steps across which recruitment might take place. To identify these parameters, the model is run with alternative values. The values that maximize the likelihood (when the likelihood model is comparable across model fits) and/or are best according to other criteria (see below), are chosen. In this work models were fitted with 3 options for the timing of these pulses τ_j. Good candidate values for the timings were determined by examination of the non-parametric catch spike statistic, defined as [13],

$$Spike_t = 10\left(\frac{\chi_t}{max(\chi_t)} - \frac{E_t}{max(E_t)}\right) \tag{2}$$

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. [26] for a graphical demonstration of the use the spike statistic. The use of the non-parametric statistic is not arbitrary because the best configuration is selected as the model with the configuration that maximizes the likelihood function.

The model in Eq. 1 describes the deterministic process that generates the expected catch under the model. The statistical framework is completed by taking the four observed catch time series as random variables whose mean time series is Eq. 1 with realized time series coming from any of a number of distributions. These distributions define the likelihood function that is to be maximized. Among these, the normal and lognormal distribution have simple formulas for the adjusted profile likelihood, an approximation that eliminates the dispersion parameter from the estimation problem. Models were fitted with the adjusted profile normal, adjusted profile lognormal, exact normal and exact lognormal likelihoods. Formulas used are all listed in [16, Table 2].

Generalized depletion models were fitted using a customized version of R package CatDyn [18]. All parameters are free parameters to be estimated, none of them is fixed at arbitrary values. The latest version also estimates fishing mortality per time step by using a numerical resolution (R function *uniroot*) of the Baranov equation from estimates of abundance, natural mortality and (observed and estimated) catch per time step. CatDyn depends on package optimx [30], 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 [12, 26, 13, 27, 14, 15, 16, 17, 18, 28]. The combination of options for timing of those pulses, likelihood function, and numerical optimization routine led to fitting 36 alternative model variants for the effort and catch (in numbers) time series. We selected the best model by employing the following numerical, biological and statistical criteria. Firstly, all fits returning a numerical gradient higher than 1 for parameters determining the estimation of abundance and biomass (M,N_0,and the 64 recruitment magnitudes) were eliminated. This is a commonly employed criterion in stock assessment [31, 32, 33, 34]. Secondly, variants yielding unrealistic values of the natural mortality rate (i.e. less than 0.1 per month) given the known lifespan of the dolphinfish 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.

Directly from results of fitting generalized depletion model, it is possible to calculate two measures of exploitation rate: aggregated (catch in numbers over abundance) and instantaneous ($F/(F+M) = F/Z$), where F is the fishing mortality rate. F is calculated in the software by resolving F from knowledge of catch (in numbers), abundance and natural mortality M using Baranov's catch equation:

$$C_{t,f} = N_t \frac{F_{t,f}}{F_{t,f}+M}(1 - e^{-(F_{t,f}+M)t}) \tag{3}$$

Both measures of exploitation rate can be used directly for management but particularly for the instantaneous exploitation rate, there is a study demonstrating that for stocks with the life history of small pelagic fish instantaneous exploitation rates less than 40% maintain a stable and sustainable spawning biomass [35]. Although the dolphinfish is not a small pelagic it has a similar life history as small pelagic fish.

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 initial abundance (i.e. in January of each year) can be obtained by rolling back recruitment pulses from the month of recruitment and adding that to abundance in December of the previous year. Rolling back entails using the natural mortality rate estimate M with reversed sign. Knowing also the mean weight per month (Fig. 4), monthly abundance can be transformed into biomass, B_t. The function CatDynBSD in CatDyn does this calculation using the delta method to propagate statistical uncertainty in N_0, M, and mean weight, to B_t. Having thus obtained the estimated biomass at each month and its standard deviation from CatDyn, the month with the lowest average standard error across the years was selected as the value of annual biomass to fit the Pella-Tomlinson production model,

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

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 annual catch during the previous fishing season.

The 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 2015 as additional data to fit the Pella-Tomlinson model. Selecting the month with the least average (across years) CV of the biomass estimate helps have more precise estimates of parameters in Pella-Tomlinson model.

The annual biomass and its standard deviation from fitting generalized depletion models and the annual biomass predicted by the Pella-Tomlinson model are linked through a hybrid (marginal-estimated) likelihood function,

$$\ell_{HL}(\boldsymbol{\theta}_{PT}|\{\hat{B}_y\}) \propto -\frac{1}{2}\sum_{y_1}^{y_{end}}\left(log(2\pi S^2_{\hat{B}_y}) + \frac{(\hat{B}_y - B_y)^2}{S^2_{\hat{B}_y}}\right) \tag{5}$$

where

- $\boldsymbol{\theta} = \{B_{y0}, K, r, p\}$ is the vector of parameters of the Pella-Tomlinson model in Eq. 4 plus one additional parameter for biomass in the year prior to the first year in the time series, 2003,
- $S^2_{\hat{B}_y}$ 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

With reference to $\boldsymbol{\theta}$, models were fitted where B_{y0} was a distinct parameter, as opposed to the usual practice of making $B_{y0} = K$ to take out one parameter from the optimization problem.

The analysis at this stage was programmed in ADMB [36] using ADMB-IDE 10.1 64 bits [37]. 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.

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.

With reference to the latent productivity [38], this is a biological reference point analogous to 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 Roa-Ureta et al. [14] we found that the stock under study was fluctuating because of a high value of the intrinsic population growth rate, r. Thus MSY was not applicable 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 harvest rates.

3 Results

3.1 Generalized depletion models

A total of 36 generalized model variants were fitted using CatDyn across the 192 months of effort and catch data by the four fleets, half of them using the *spg* and half the *CG* numerical methods for optimization. Initially, a set of 32 variants were fit with a specific assumption regarding the timing of the 64 recruitment events. Only two of those variants yielded a natural mortality rate higher than 0.1 per month and all variants predicted unrealistically high biomass. Three variants, characterized by the following specifications:

- variant 25: CG optimization algorithm, adjusted profile normal for the Peruvian artisanal fleet and the Peruvian fibreglass fleet, adjusted profile lognormal for the Ecuadorian artisanal fleet and the Ecuadorian fibreglass fleet,

- variant 29: CG optimization algorithm, adjusted profile normal for the Peruvian artisanal fleet, the Peruvian fibreglass fleet, the Ecuadorian artisanal fleet, and adjusted profile lognormal for the Ecuadorian fibreglass fleet,

- variant 31: CG optimization algorithm, adjusted profile normal for the catch data off all fleets,

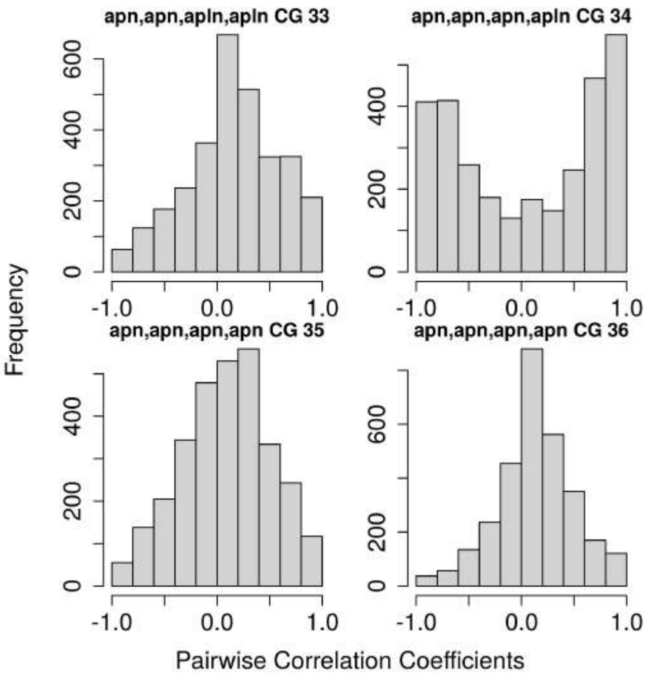

Figure 6: Correlation structure of estimates of the short list of four best variants of generalized depletion models fitted to catch data of the four fleets. The title of each histogram indicates the likelihood model (apn is adjusted profile normal and apln is adjusted profile lognormal for each fleet, numerical algorithm used for optimization, and model variant number

yielded the lowest biomass estimates and one of them also yielded a higher natural mortality estimate. These three variants were re-fitted using different starting values for recruitment parameters leading to variants 33, 34 and 35. These three additional variants yielded realistic biomass predictions and realistic natural mortality rate estimates. Variant 35 yielded the best correlation structure (Fig. 6) and lowest standard error of estimates. Small adjustments to the timing of some recruitment events in variant 35 led to fitting variant 36.

The AIC, useful to compare variants 35 and 36 because they were fit with the same likelihood model, was not conclusive. Nevertheless, variant 36 had only two gradients (for β of the Peruvian artisanal fleet and k of the Ecuadorian fibreglass fleet) larger than 1, less than all other 35 variants. Furthermore, had the best correlation structure (Fig. 6), reasonable natural mortality rate estimate and biomass predictions, and high statistical precision of the estimates for natural mortality rate and initial abundance, N_0. Thus variant 36 was selected as the best generalized depletion model to fit the catch data of the four fleets.

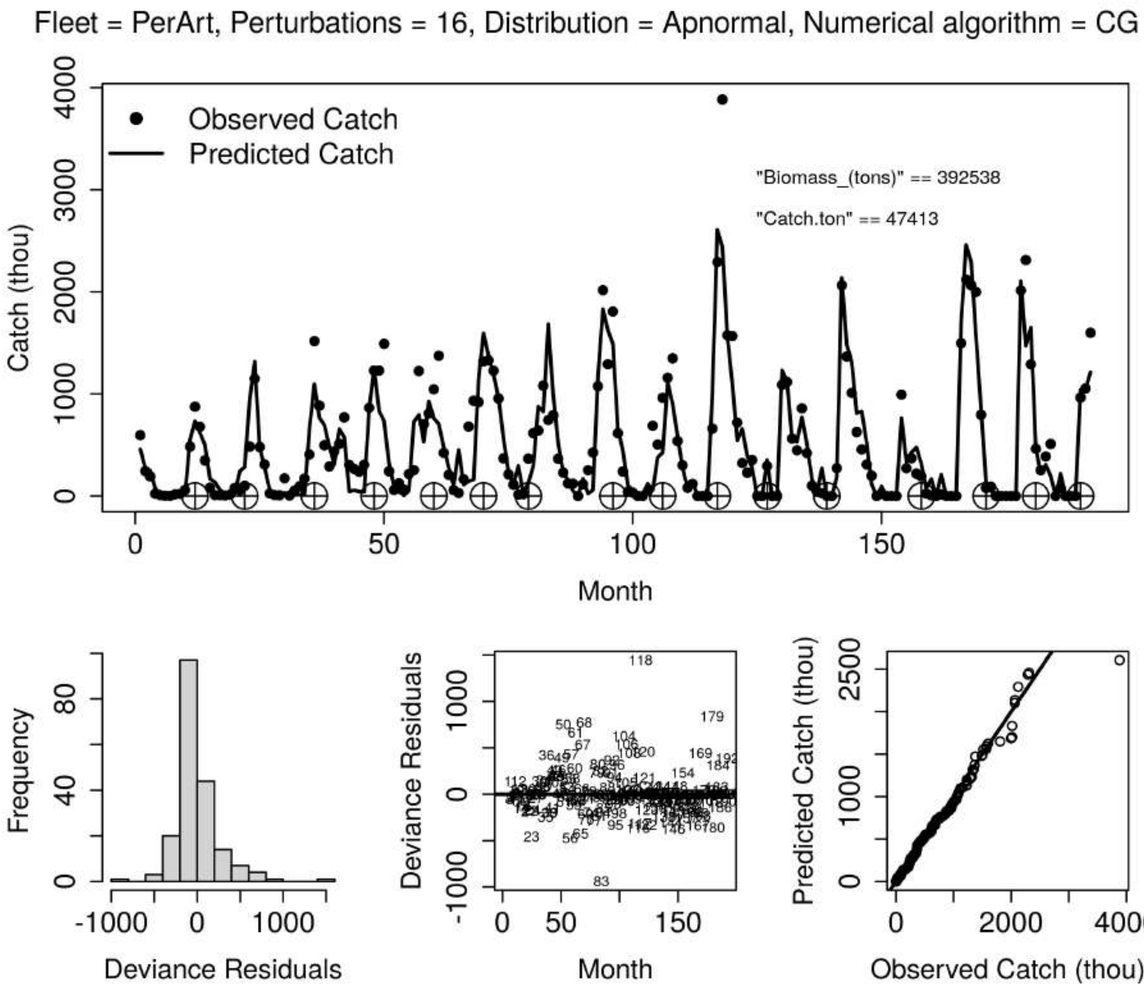

Figure 7: Top panel: Fit of the generalized depletion model to the Peruvian artisanal fleet catch data (top panel), with target symbols indicating the timing of annual recruitment. The catch is the total catch by all fleets in the last year, and the biomass is the biomass at the last month of the times series (December 2019). Bottom panels: from left to right, histogram of deviance residuals, deviance residual cloud, and quantile-quantile plot.

Table 1: Directly estimated parameters corresponding to the Peruvian artisanal fleet of the best generalized depletion model (variant 36) fitted the 192 months (2004 to 2019) of effort and catch data of the the dolphinfish fishery in the South-East Pacific. Variant 36 was fitted with the adjusted profile normal distribution for all four fleets, the CG numerical algorithm, recruitment timings as suggested by the catch spike statistic with a few adjustments. MLE: maximum likelihood estimate. CV: coefficient of variation. CVs not shown correspond to optimization failures for second order properties at particular parameters.

Parameter	**Timing**	**MLE**	**CV** (%)
M (month^{-1})		0.3390	5.0
N_0 (thousand)		99,934	18.3
Recruitment 2004 (thousand)	2004-12	155,253	
Recruitment 2005 (thousand)	2005-10	206,925	
Recruitment 2006 (thousand)	2006-12	155,811	
Recruitment 2007 (thousand)	2007-12	31,642	
Recruitment 2008 (thousand)	2008-12	7,619	275.4
Recruitment 2009 (thousand)	2009-10	143,019	98.4
Recruitment 2010 (thousand)	2010-7	425,94	143.6
Recruitment 2011 (thousand)	2011-12	1,484	316.6
Recruitment 2012 (thousand)	2012-10	88,123	50.6
Recruitment 2013 (thousand)	2013-9	298,651	14.6
Recruitment 2014 (thousand)	2014-7	579,369	14.0
Recruitment 2015 (thousand)	2015-7	3,319	279.0
Recruitment 2016 (thousand)	2017-2	586	228.6
Recruitment 2017 (thousand)	2018-3	5,879	200.4
Recruitment 2018 (thousand)	2019-1	666	317.5
Recruitment 2019 (thousand)	2019-10	321,265	
k (1/days)		0.00008558	
α		0.9443	
β		0.7060	

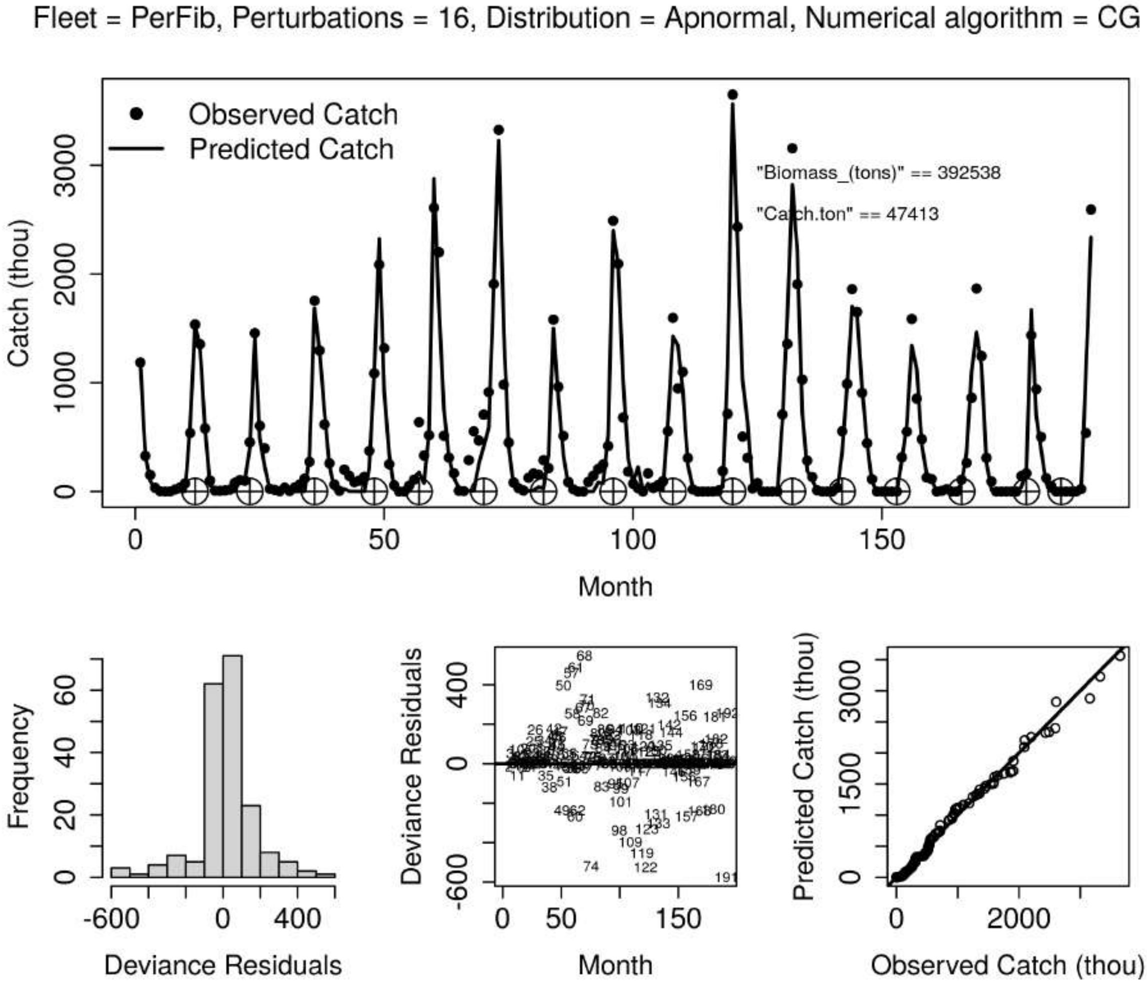

Figure 8: Top panel: Fit of the generalized depletion model to the Peruvian fibreglass fleet catch data (top panel), with target symbols indicating the timing of annual recruitment. The catch is the total catch by all fleets in the last year, and the biomass is the biomass at the last month of the times series (December 2019). Bottom panels: from left to right, histogram of deviance residuals, deviance residual cloud, and quantile-quantile plot.

Table 2: Directly estimated parameters corresponding to the Peruvian fibreglass fleet of best generalized depletion model fitted (variant 36) the 192 months (2004 to 2019) of effort and catch data of the the dolphinfish fishery in the South-East Pacific. MLE: maximum likelihood estimate. Variant 36 was fitted with the adjusted profile normal distribution for all four fleets, the CG numerical algorithm, recruitment timings as suggested by the catch spike statistic with a few adjustments. CV: coefficient of variation. CVs not shown correspond to optimization failures for second order properties at particular parameters.

Parameter	**Timing**	**MLE**	**CV** (%)
M (month^{-1})		0.3390	5.0
N_0 (thousand)		99,934	18.3
Recruitment 2004 (thousand)	2004-12	13,205	
Recruitment 2005 (thousand)	2005-11	20,169	
Recruitment 2006 (thousand)	2006-12	13,121	
Recruitment 2007 (thousand)	2007-12	66,906	
Recruitment 2008 (thousand)	2008-9	223,212	21.2
Recruitment 2009 (thousand)	2009-10	8,744	1118.5
Recruitment 2010 (thousand)	2010-10	48,159	65.6
Recruitment 2011 (thousand)	2011-12	1,292	340.6
Recruitment 2012 (thousand)	2012-12	68,577	
Recruitment 2013 (thousand)	2013-12	740	246.1
Recruitment 2014 (thousand)	2014-12	23,045	92.5
Recruitment 2015 (thousand)	2015-10	119,023	21.1
Recruitment 2016 (thousand)	2016-9	107,607	24.1
Recruitment 2017 (thousand)	2017-10	215,594	14.8
Recruitment 2018 (thousand)	2018-11	127,903	18.1
Recruitment 2019 (thousand)	2019-7	3,421	384.8
k (1/days)		0.0000003386	
α		1.0901	2.3
β		1.2360	0.1

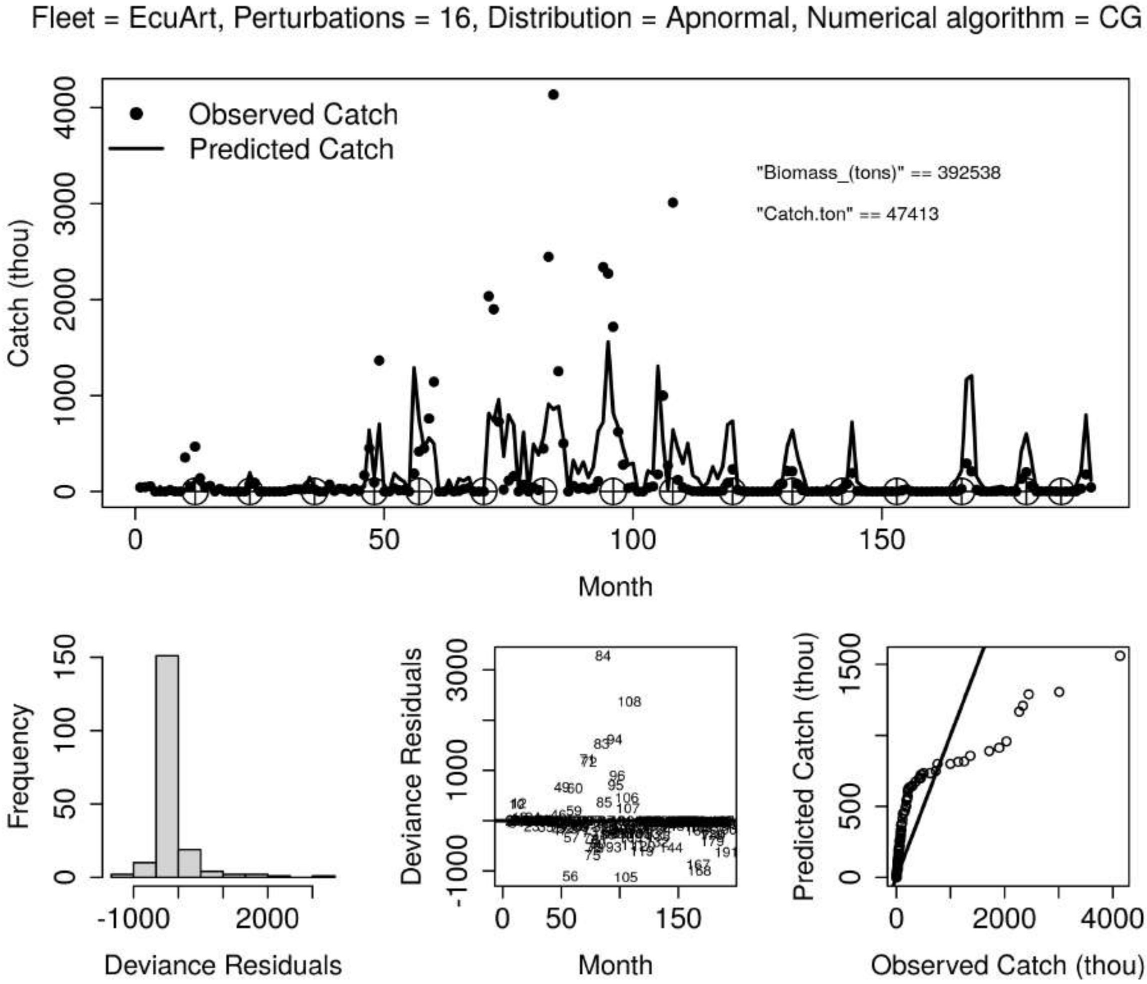

Figure 9: Top panel: Fit of the generalized depletion model to the Ecuadorian artisanal fleet catch data (top panel), with target symbols indicating the timing of annual recruitment. The catch is the total catch by all fleets in the last year, and the biomass is the biomass at the last month of the times series (December 2019). Bottom panels: from left to right, histogram of deviance residuals, deviance residual cloud, and quantile-quantile plot.

Table 3: Directly estimated parameters corresponding to the Ecuadorian artisanal fleet of best generalized depletion model fitted (variant 36) the 192 months (2004 to 2019) of effort and catch data of the the dolphinfish fishery in the South-East Pacific. MLE: maximum likelihood estimate. Variant 36 was fitted with the adjusted profile normal distribution for all four fleets, the CG numerical algorithm, recruitment timings as suggested by the catch spike statistic with a few adjustments. CV: coefficient of variation. CVs not shown correspond to optimization failures for second order properties at particular parameters.

Parameter	**Timing**	**MLE**	**CV** (%)
M (month^{-1})		0.3390	5.0
N_0 (thousand)		99,934	18.3
Recruitment 2004 (thousand)	2004-11	7,646	
Recruitment 2005 (thousand)	2005-12	4,384	
Recruitment 2006 (thousand)	2006-12	7,734	
Recruitment 2007 (thousand)	2007-12	25,468	58.0
Recruitment 2008 (thousand)	2009-1	4,620	1540.8
Recruitment 2009 (thousand)	2009-10	24,218	
Recruitment 2010 (thousand)	2010-12	149,946	20.5
Recruitment 2011 (thousand)	2011-10	6,993	
Recruitment 2012 (thousand)	2012-12	43,867	23.8
Recruitment 2013 (thousand)	2014-1	3,693	
Recruitment 2014 (thousand)	2015-3	30,006	24.8
Recruitment 2015 (thousand)	2016-1	1,233	384.3
Recruitment 2016 (thousand)	2016-12	1,226	2460.6
Recruitment 2017 (thousand)	2017-7	476	377.7
Recruitment 2018 (thousand)	2019-1	1,184	679.6
Recruitment 2019 (thousand)	2019-7	1,487	
k (1/days)		0.0001268	
α		2.0424	4.3
β		0.5236	14.4

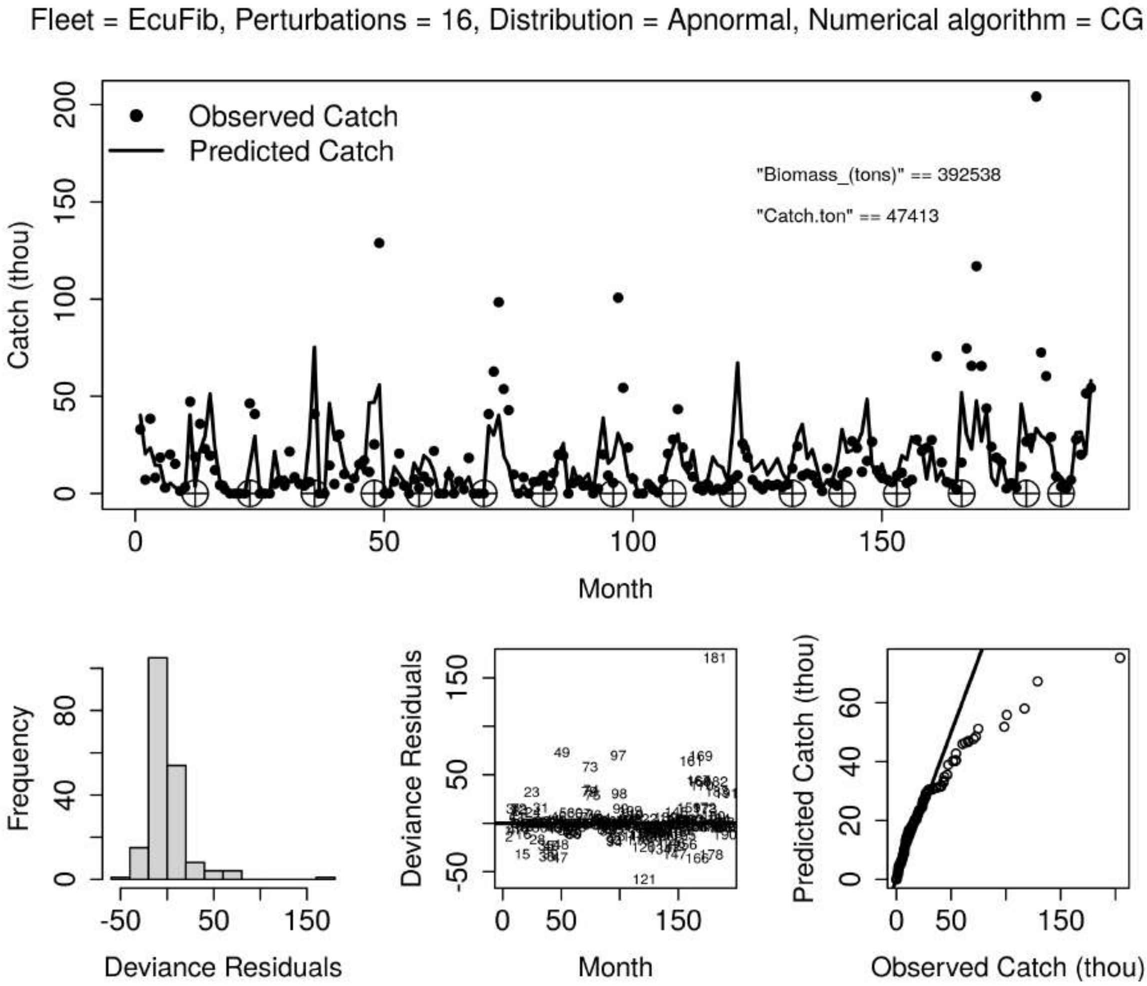

Figure 10: Top panel: Fit of the generalized depletion model to the Ecuadorian fibreglass fleet catch data (top panel), with target symbols indicating the timing of annual recruitment. The catch is the total catch by all fleets in the last year, and the biomass is the biomass at the last month of the times series (December 2019). Bottom panels: from left to right, histogram of deviance residuals, deviance residual cloud, and quantile-quantile plot.

Table 4: Directly estimated parameters corresponding to the Ecuadorian fibreglass fleet of best generalized depletion model fitted (variant 36) the 192 months (2004 to 2019) of effort and catch data of the the dolphinfish fishery in the South-East Pacific. Variant 36 was fitted with the adjusted profile normal distribution for all four fleets, the CG numerical algorithm, recruitment timings as suggested by the catch spike statistic with a few adjustments. MLE: maximum likelihood estimate. CV: coefficient of variation. CVs not shown correspond to optimization failures for second order properties at particular parameters.

Parameter	**Timing**	**MLE**	**CV** (%)
M (month^{-1})		0.3390	5.0
N_0 (thousand)		99,934	18.3
Recruitment 2004 (thousand)	2004-12	7,646	
Recruitment 2005 (thousand)	2005-12	16,980	
Recruitment 2006 (thousand)	2007-1	68,377	48.0
Recruitment 2007 (thousand)	2008-1	2,696	536.1
Recruitment 2008 (thousand)	2008-12	88,454	48.5
Recruitment 2009 (thousand)	2009-11	44,985	
Recruitment 2010 (thousand)	2010-12	36,395	28.0
Recruitment 2011 (thousand)	2012-1	6,424	
Recruitment 2012 (thousand)	2013-1	693	254.4
Recruitment 2013 (thousand)	2013-12	2,655	
Recruitment 2014 (thousand)	2014-11	2,232	365.5
Recruitment 2015 (thousand)	2015-12	35,557	25.6
Recruitment 2016 (thousand)	2017-1	5,575	
Recruitment 2017 (thousand)	2017-12	503	367.0
Recruitment 2018 (thousand)	2019-1	2,101	
Recruitment 2019 (thousand)	2019-11	2,779	
k (1/days)		0.001884	176.3
α		0.9377	14.8
β		0.3131	37.4

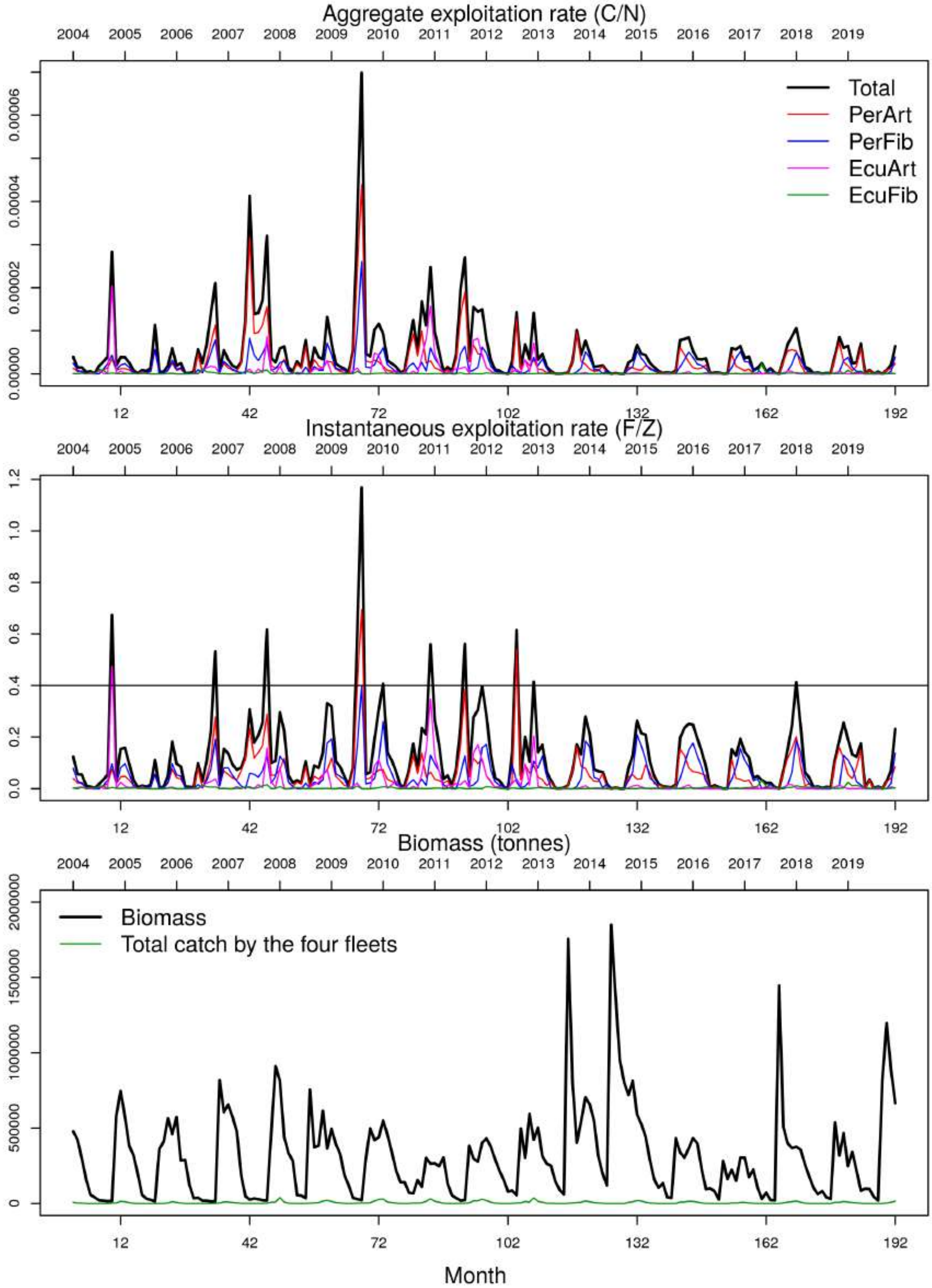

Figure 11: Top panel: Aggregate exploitation rate for each fleet and in total. Middle panel: instantaneous exploitation rate per fleet and in total. Bottom panel: stock biomass and catch in weight.

The fit of variant 36 to the data from the four fleets is shown in Figs. 7-10. It can be seen in Fig. 7 that the selected model closely follows the catch data from the Peruvian artisanal fleet. Diagnostics plots at the bottom panels show good consistency with the model's assumptions, with a symmetric histogram of residuals, a shapeless cloud of residuals, and a diagonal quantile-quantile plot. "Biomass" is predicted biomass in the last month, December 2019, and "Catch" is the total catch by the four fleets in the last year, 2019.

The model indicates that the catch taken during the last year of the time series was only 12% of the biomass left available at the end of the year, which is a very moderate exploitation rate. The fit of the model to the data from the Peruvian fibreglass fleet is even better (Fig. 8), with excellent agreement between model and data (top panel), symmetrical residual histogram, shapeless residual cloud, and excellent quantile-quantile plot. However, the fit of the model to the Ecuadorian artisanal fleet (Fig. 9) much poorer, with numerous high catches that are not well followed by the model (top panel), skewed residual histogram, and far from diagonal quantile-quantile plot. The fit of the model to the Ecuadorian fibreglass fleet (Fig. 10) is somewhat better though still poor, with numerous high catches not well predicted by the model (top panel), slightly skewed residual histogram (month 181 is a highly positive residual), nearly shapeless residual cloud (except for month 181), and nearly all lower quantiles following on the diagonal.

Parameter estimates from the selected generalized depletion model are presented in Tables 1-4. Monthly natural mortality M is very high, as expected considering the short life history of the dolphinfish [11]. Initial abundance N_0 was in the order of a hundred million. Recruitment estimates to the Peruvian artisanal fleet (Table 1) vary from a few million to several hundred million. Catches are nearly proportional to effort and hyper-stable to abundance. Recruitment estimates to the Peruvian fibreglass fleet (Table 2) vary from a few hundred thousand to a few hundred million. Catches are nearly proportional to both effort and abundance. Recruitment estimates to the Ecuadorian artisanal fleet (Table 3) vary from a few hundred thousand to a few tens of million. Catches are synergistic to effort and hyper-stable to abundance. Recruitment estimates to the Ecuadorian artisanal fleet (Table 3) vary from a few hundred thousand to a few tens of million. Catches are proportional to effort and hyper-stable to abundance. Many standard errors (and thus CVs) could not be calculated signifying problems with the curvature of the likelihood function close to the maximum.

The aggregate exploitation rate is very low, reaching a maximum of 0.006% fish caught with respect to total abundance happening over the sixth year of the time series, while usually at every month total catch takes 0.0002% of all available fish (Fig. 11, top panel). The instantaneous exploitation rate (Fig. 11, middle panel) remains most of the months under 40%, the reference point obtained by Patterson [35], crossing that threshold just a few times and for one-month periods. The biomass and catch time series shows that at specific months in each year total catch in biomass approaches stock biomass while most of the months the latter is much higher than the former.

3.2 Population dynamics models

Estimation of the biomass monthly time series and the standard error of biomass estimates using the function CatDynBSD in the extended CatDyn software yielded estimates that on average, were most precise in the month of November, with an average CV of 225%, which is quite imprecise although less imprecise than in other months. Thus, the biomass estimate in November was selected to fit Pella-Tomlinson surplus production model.

Fig. 12 shows the fitted Pella-Tomlinson dynamics as well as biomass estimates from the best generalized depletion model and the time series of total annual catch. Biomass estimates from CatDyn running in R and the Pella-Tomlinson surplus production biomass running in ADMB show good agreement. The Pella-Tomlinson model shows that the stock has a tendency to undergo marked fluctuations and that the most recent status of the stock is the most uncertain part of the time series. The stock biomass has been well above landings for a long period that ended in 2016, when there was a sharp drop in biomass. This observed decline in biomass was followed by an equally fast recovery in stock biomass over the next 2 years. Overall, stock biomass shows fluctuation about a constant mean close to 350 thousand tonnes.

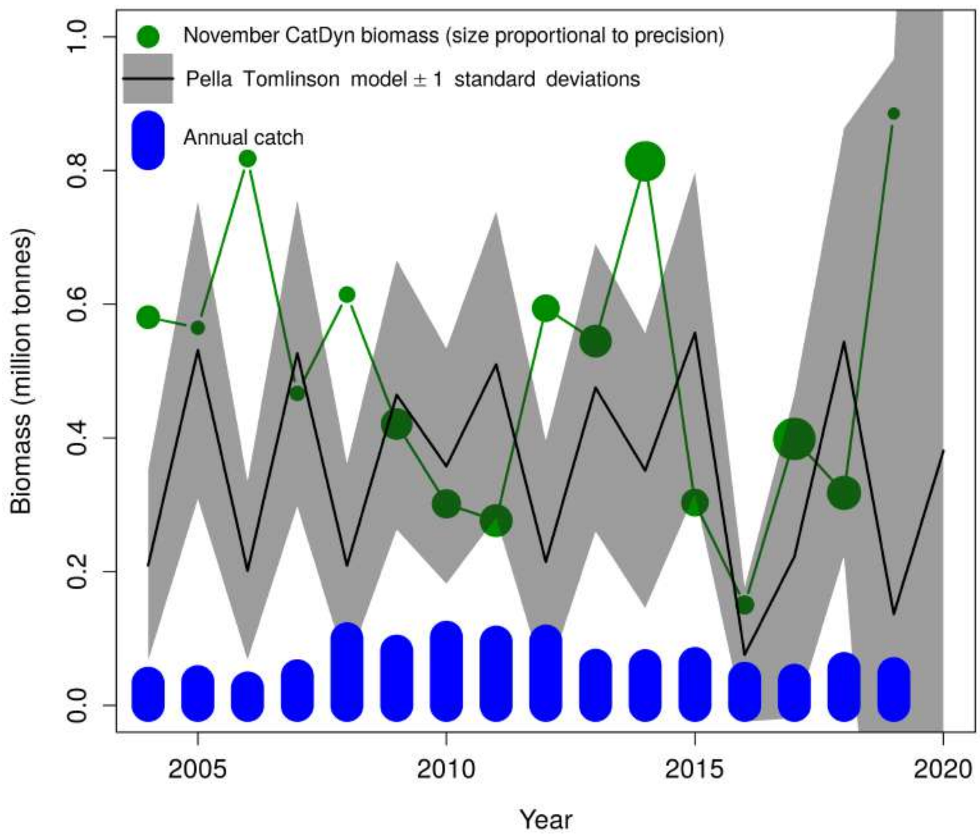

Figure 12: November stock biomass estimated by generalized depletion model variant 36 (extended CatDyn software), total annual catch by four fleets, and fitted Pella-Tomlinson model of population dynamics of the dolphinfish in the South-Easter Pacific.

Parameters of the Pella-Tomlinson model were fitted with good precision (Table 5), both those directly estimated by optimization and the derived parameters MSY, B_{MSY} and $B_{\dot{P}}$. The exception is the average total latent productivity (average latent productivity +

landings) which is estimated with poor precision. The MSY estimate is very high, actually six times higher than the average catch of the four fleets over the time series. Conversely, the total average latent productivity a little double the average catch of the four fleets over the time series. This is because the stock has a fluctuating dynamics and therefore the MSY is not applicable. The total average latent productivity is the sustainable harvest rate for fluctuating stocks. Both the estimated intrinsic rate of population growth r and the symmetry of the production function p are high, making the stock highly productive.

Table 5: Directly estimated parameters from the Pella-Tomlinson model (r, p and K) and derived biological reference points (MSY and B_{MSY}) for the dolphinfish in the South-East Pacific (Peru and Ecuador) according to parameterization in Eqs. 4, 6-8 with ADMB code.

Parameter	**Concept**	**Estimate**	**Standard error**	**CV** (%)
r (yr^{-1})	Intrinsic growth rate	2.7783	1.96450	70.7
p	Production function symmetry	2.2063	0.61208	27.7
K (tonnes)	Environmental carrying capacity	456,960	187,860	41.1
B_{2003} (tonnes)	Initial biomass	209,590	142,470	68.0
MSY (tonnes)	Maximum sustainable yield	360,225	194,422	54.0
B_{MSY} (tonnes)	Biomass at MSY	237,131	102,124	43.1
$\dot{P}$ (tonnes)	Average total latent productivity	152,980	562,595	367.8
$B_{\dot{P}}$ (tonnes)	Average biomass at $\dot{P}$	349,218	238,525	68.3

4 Discussion

This study shows that the stock of the dolphinfish in the South-East Pacific was being being harvested in sustainable fashion up to the last year of the available time series of data (2019). In fact, average landings by the four fleets over the 2004 to 2019 period are below half of the sustainable harvest rate, estimated at 152,980 tonnes of total average latent productivity, and therefore the stock may sustain higher catches. Aires-da-Silva *et al.* [20] have described the combined Peruvian-Ecuadorian fishery as a data poor fisheries and have characterized the stock dynamics as highly productive, variable and fast. Our results confirm that description by showing that the stock has a high intrinsic rate of population growth (r) making it a resilient stock, that may recover quickly from low biomass, high mortality rate and fast biomass production function. In addition, the stock has a high symmetry of the production function (p), exceeding the value of 2 which corresponds to a symmetric production function. Therefore the stock has the highest growth rate at biomass higher than $K/2$, meaning that it is advisable to keep the stock at high biomass levels to harvest the maximum surplus.

In their assessment of the same stock Aires-da-Silva *et al.* [20] concluded that the stock was being harvested at close to MSY levels. Our results here support the overall conclusion that the stock is not overfished and not experiencing overfishing but they also indicate that the current harvest is well below maximum sustainable harvest rates. The difference in results may arise from a number of issues acting in conjunction or separately.

First, we used different data. Our database was more extended (from January 2004 to December 2019) than the database compiled by Aires-da-Silva *et al.* (July 2007 to June 2015). In addition, for the period covered by Aires-da-Silva *et al.* we have higher catches from Ecuadorian fleets between 2008 and 2012.

Second, the stock assessment by Aires-da-Silva *et al.* is based on length frequency data and CPUE indices of relative abundance while our assessment is based on the effort-catch dynamics (generalized depletion models) and the aggregate biomass dynamics (Pella-Tomlinson surplus production model). Aires-da-Silva *et al.* length-structured model is more complex from the population dynamics point of view and it has to make several assumptions to simplify the problem. Authors list 8 such assumptions but principal among these are three:

- Fixed natural mortality rate (M = 1 yr^{-1} for both sexes);
- Fixed Steepness (h) of the stock-recruitment relationship (h = 1); and
- The CPUE time series of the Ecuadorian artisanal fishery was chosen as the most reliable index of abundance to calibrate the stock assessment model. For this reason, its coefficient of variation (CV) was fixed at 0.2.

In this work we have estimated the natural mortality rate from the data, inside the stock assessment model, by maximum likelihood and this objective estimate turned out to be much higher that the value assumed by Aires-da-Silva *et al.*. Fixing natural mortality too low in a stock assessment would lead to under-estimation of fish abundance because less fish are needed to explain catches. This alone could explain why Aires-da-Silva *et al.* obtained less dolphinfish abundance than in our assessment. Fixing the steepness at a very high value, as done by Aires-da-Silva *et al.*, would ameliorate somewhat the under-estimation of abundance due to a low fixed value for natural mortality but our results show that the natural mortality rate is over 3 times higher than the value assumed by Aires-da-Silva *et al.* so any amelioration caused by fixing the steepness very high may not be sufficient to compensate for a too low natural mortality rate. Furthermore, the decision by Aires-da-Silva *et al.* to give more weight to the Ecuadorian CPUE index of abundance because it seemed to produce a best fit in their assessment, may not have been the best decision. In our analysis, we used a catch and effort database compiled by Ecuadorian experts that differed substantially from the time series used by Aires-da-Silva *et al.*, especially between 2008 and 2012. Thus their better fit to Ecuadorian CPUE would be an artifact of missing catch data. In addition, our results also show that the Ecuadorian data, from both fleets, is less well fit to depletion models because of more extreme (high) values of catch. This characteristic of the Ecuadorian data may have affected the assessment by Aires-da-Silva *et al.*.

Third, we distinguished four fleets operating in the fishery, two in each country EEZ, while Aires-da-Silva *et al.* aggregated all national fleets and added a third fleet (tuna purse seiners) yielding bycatch of dolphinfish. It seems to us that separating the artisanal and fibreglass fleets inside country fleets, as they operate in much different ways, is more important than adding bycatches that account for just 2% of total catches. The artisanal fleets of both countries may conduct long fishing trips, extending over several days, in oceanic waters while fibreglass boats can only operate in coastal waters for short fishing trips.

Therefore, although it is re-assuring that both Aires-da-Silva *et al.* and this work conclude that the dolphinfish stock in the South-East Pacific is not overfished and it is not undergoing over-fishing, we believe our results showing that current harvest rates are well below maximum sustainable rates, stand on more solid ground.

Although the estimation of Pella-Tomlinson model was achieved with good statistical precision of all four parameters directly estimated r, p, K, and B_2003) as well as derived parameters MSY, B_{MSY}, and $B_{\dot{P}}$, the estimation of the total average latent productivity was imprecise. This is probably the most important biological reference point from the assessment because it directly indicates sustainable harvest rates that could be considered as limit catches. For instance, Peru and Ecuador may agree on a partitioning of the total average latent productivity and then set Total Allowable Catches (TAC) at the national level using their partition of the total average latent productivity. Therefore it is very relevant to improve the estimation of the total average latent productivity in order to improve statistical precision. This could be achieved in two different, and possibly complementary ways.

First, and without much additional effort, it is possible to simply extend the total annual catch data for both countries as much into the past as possible, and then re-fit Pella-Tomlinson model with these additional data. This would probably lead to better statistical precision of biomass estimates from ADMB and therefore better precision of the total average latent productivity.

Second, annual biomass estimates from CatDyn from November, used to fit the Pella-Tomlinson model, were quite imprecise. Those biomass estimates could probably improve in terms of statistical precision by improving the mean monthly weight data, which is highly variable especially for Ecuadorian fleets at the end of the time series. Since Ecuadorian data is actually mean length data and the length-weight relationship from the dolphinfish in Baja California Sur was used to transform it to weight, it is very likely that the mean weight data from the catches of Ecuadorian fleets would improve by using a length-weight relationship derived from Ecuadorian data. Having that local length-weight relationship and using it to transform Ecuadorian mean monthly length into mean monthly weight would entail re-fitting generalized depletion models and then re-fit the Pella-Tomlinson model. However, that would not take much extra effort because although each run of the statistical optimization to fit generalized depletion models takes hours, it is possible to use the likelihood combination that have already proven to be better for the data. Therefore only a few new runs of the optimization would be needed.

Improving stock assessment results can be accomplished fairly easily given these additional data components (total annual landings prior to 2004 and Ecuadorian length-weight relationship) though this will most likely just increase the precision of important estimates, such as the total average latent productivity, without changing much the overall status of the stock. In this connection, it should be emphasized that any action to increase effort to take more of the sustainable productive capacity of the stock, up to the estimated total average latent productivity, should be done gradually and implementing updated stock assessments every new year, to monitor the condition of the stock continuously. Here we have provided a stock assessment methodology and its software to conduct the assessment on a regular basis, ideally annually, as the dynamics of short-lived stocks requires frequent stock assessment updates.

5 Conclusions

1. A stock assessment database of monthly catch, effort and mean weight data for the dolphinfish in the South-East Pacific (Peru and Ecuador) with the activity of four longline fleets, spanning 2004 to 2019, has been compiled from the data collection programs of IMARPE and IPIAP experts.

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 dolphinfish in the South-East Pacific (Peru and Ecuador) as more data are collected.

3. The stock assessment methodology was applied to the dolphinfish in the South-East Pacific (Peru and Ecuador) data and the four fleets generating results with a generally acceptable level of statistical precision and biological realism.

4. The implementation of the methodology can be substantially improved by continuing the same data collection programs that led to the 2004-2019 database and extending the time series of available data in the database.

5. Among a set of 36 variants of generalized depletion models, defined by 32 combinations of likelihood functions per fleet and numerical method of optimization, plus 4 adjustments to initial values and some months of recruitment, the best model was one with normal distributions for the data from all four fleets and CG numerical optimization algorithm.

6. Natural mortality rates are very high (0.339 per month) and estimated with good statistical precision (5% CV), annual recruitment pulses to the whole region and the four fleets vary from a few million to a few hundred million fish, and catches are generally proportional to fishing effort and hyper-stable to abundance.

7. Aggregate and instantaneous exploitation rates (as well as fishing mortality) were well within sustainable levels for the whole length of the time series 2004-2019.

8. The stock in the region has a high intrinsic rate of population growth and asymmetric biomass production function, making it resilient and prone to undergo large fluctuations in biomass.

9. Due to fluctuating dynamics, the mean total latent productivity was determined to be the adequate sustainable harvest rate of the stock, evaluated at 152,900 tonnes per year, though the estimate is affected by large statistical uncertainty.

6 Management Advice

This management advice is exclusively in relation to the biological condition of the stock of dolphinfish in the South-East Pacific and to key fishery factors such as fishing mortality. Thus it is made without consideration of the wider context of the fishery, such as ecosystem, social and economic indicators, among others.

1. Continue the data collection program and the growth of the stock assessment database to update the assessments regularly and improve the statistical precision of some biological references points.

2. Explore further improvements in the stock assessment database by extending the total annual landings prior to 2004 and by introducing a local length-weight relationship for the fish captured by Ecuadorian fleets.

3. Update the stock assessment with data from 2020 and the data items above and confirm the status of the fishery.

4. Conditional upon confirmation with further data of the status of the stock, develop a plan to gradually increase fishing effort and thus yield better outcomes from the fishery for fishers, consumer and exporters, up to a level below the level required to harvest the total average latent productivity annually.

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References

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