Stock Assessment of *Octopus cyanea* in the fishery of Southwest Madagascar, 2015 to 2020

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1 Executive Summary

A stock assessment database of total catch, total fishing effort and mean weight per week of fishing from 2015 to 2020 was built based on three databases built by Blue Ventures with a coverage of 41% in 2015, 24% in 2016, 20% in 2017, 6% in 2018, 3% in 2019, and 4% in 2020, of the total annual catch as recorded by official sources.

These databases for stock assessment have proven useful to fit intra-annual generalized depletion (IAGD) models to the data of each year of fishing separately, although the drop in coverage of the sampling of the total catch in recent years have resulted in the inability to estimate the natural mortality rate, and therefore instantaneous exploitation rates, in 2019 and 2020.

IAGD models analyze the connection between total weekly catch and total weekly effort in mechanistic models of depletion and replenishment to estimate natural and fishing mortality, stock's total abundance, the magnitude of pulses of recruitment into the fishing grounds during each annual season, and fishing operational parameters. These models are particularly useful for data-limited fisheries as they do not need to use biological composition data (such as age or length frequencies) or fisheries-independent data (such as those provided by scientific surveys). IAGD models are fitted to total catch, total effort and mean weight in the catch per week in open source scientific software that is freely available and thoroughly peer-reviewed.

In general, IAGD models fitted to data in this study produced predicted total catch that closely follows observed total catch in all annual seasons covered in the study. The average natural mortality rate in the seasons when this parameter of population dynamics was well estimated (2015, 2016, 2017, and 2020) was 0.025 per week, or 1.3 per year, well in line with previous estimates for octopus stocks in other regions and in agreement with the well known life history of the stock. The fishing mortality rate exceeded the natural mortality rate only in season 2019, although this undesirable outcome probably also happened in seasons 2018 and 2020, when the natural mortality rate could not be well estimated, because the total catch in 2018 and 2019 was much higher than in 2015, 2016 and 2017. Recruitment pulses to the fishing grounds range from a few hundred thousand to a few million octopus and they occur in number ranging from two to five in each season. These recruitment pulses are most likely originated in expansions of the fishing grounds by the fishers since there was no evidence of a regular entry of juveniles at certain times of the year.

Although the number of years in the time series (6, from 2015 to 2020) is still low for a full understanding of population dynamics, it appears that the stock is entering a period of biomass fluctuations driven by increasing magnitude (total removals) and intensity (fishing mortality) of fishing in the three most recent years. Therefore it would be prudent to halt the increase in catches until further data is assembled and made available for stock assessment. In the same vein, it seems necessary to upscale the coverage of the sampling of the catch by Blue Ventures in order to increase the capacity of IAGD to estimate natural mortality and from there estimation of instantaneous exploitation rates.

2 Introduction

Small-scale fisheries (SSF) are crucial to food security and to the livelihood of coastal communities worldwide. Up to 2013, they comprised nearly 80% of global fishery catch [1] and 90% of employment in the fisheries sector [2]. These fisheries also are the vast majority of fisheries lacking in scientific management [1]. Consequently, they are facing a higher risk of unsustainable fishing practices and intensities and more obstacles to certification. One of the main causes of the lack of scientific analysis of these fisheries is that conventional stock assessment methods have been developed for large-scale fisheries (LSF) and are in general not applicable to SSF due to their prohibitive costs [3]. Given this situation, there has been a sustained effort in the fishery science community to develop stock assessment methods that can be applied to stocks fished in SSFs and that provide the same degree of knowledge and scientifically-based management that has been achieved in LLF [4].

Among these new methods to assess stocks fished by SSFs, generalized depletion models have been shown to be applicable and useful for management to a wide range of fisheries for fish and invertebrates [5, 6, 7, 8, 3, 9, 10, 11, 12, 13, 14, 15, 16]. These models provide a mechanistic description of the fishing dynamics and are applicable with elementary fisheries data, namely records of total catch, total fishing effort, and sample mean weight of organisms in the commercial catch, aggregated at rapid time steps such as daily, weekly or monthly. They produce results useful for management either as stand-alone models after the first year of collecting elementary fisheries data, or combined with conventional stock assessment models based on fish population dynamics when the time series of elementary fisheries data covers several years of fishery records.

The fishery for the octopus (*Octopus cyanea*) in Southwest Madagascar (Fig. 1) is a small-scale fishery conducted by individual fishers that hunt for individual octopus along inter-tidal coral reefs and rocky habitats. The fishing is conducted by free diving and foot fishing/gleaning and it does not extend to sub-tidal and deeper depths to a significant degree. Blue Ventures (BV) started to work with coastal communities in Southwest Madagascar in 2003 and by the first half of the 2010s, BV started building a database of fishery operations to help local coastal communities improve their octopus fishing practices and achieve sustainable exploitation of their resource through scientific studies, including stock assessment studies. This database started to have sufficiently solid data for stock assessment with depletion models in 2015.

In 2018 I conducted a stock assessment with generalized depletion models using data from seasons 2015 and 2016. Conclusions from that study included moderately low instantaneous exploitation rates (35% in 2015 and 19% in 2016), therefore the stock did not experience overfishing during the two years analyzed. Importantly, the study showed that the data collected by BV and stock assessment with these depletion models work for providing scientific evidence useful to management.

BV continued with its data collection program and currently four more seasons (2017 to 2020) of fisheries operation and biological data are available for stock assessment. This work presents the updated assessment of the stock to its condition in 2020 using generalized depletion models as stand-alone tools to discern exploitation rates and stock's abundance.

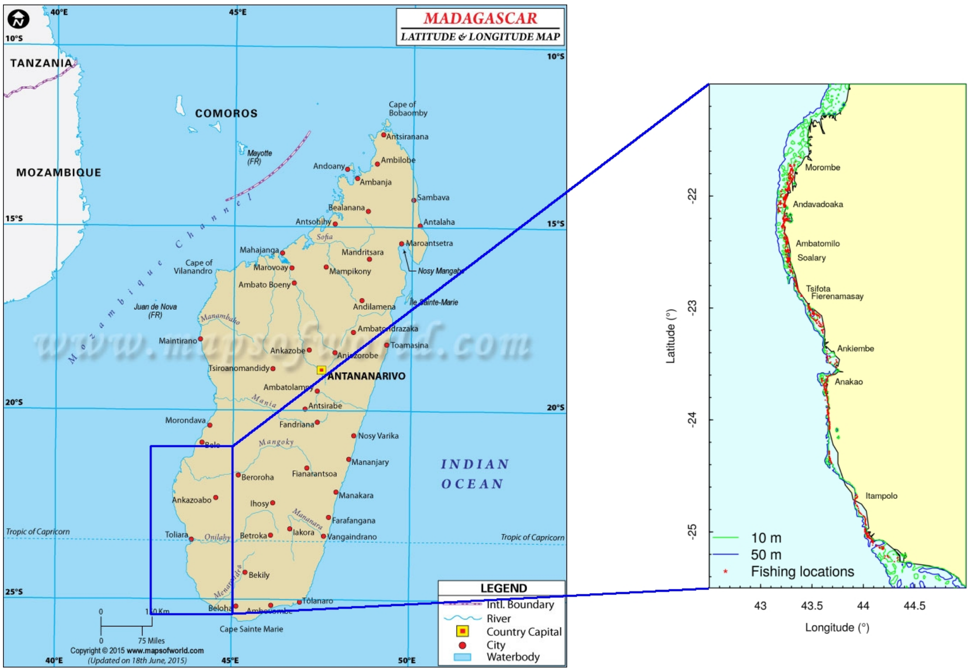


Figure 1: Map of Madagascar and location of fishing grounds in Southwest Madagascar as recorded in 2014. Coastal villages with more than 1,000 inhabitants are also shown. In the north, only the largest village (out of 6 villages with more than 1,000 inhabitants) is shown.

3 Materials and Methods

The general methodological approach to the stock assessment of the octopus in Southwest Madagascar consists of four stages.

1. Developing and curating a database of weekly catch, fishing effort, and sampled mean weight of individual octopus caught by fishers for the period of January 2015 to December 2020 in the data recorded by BV from a large sample of fishing trips.

2. Raising the total catch and total effort in the large sample to the regional total (all SW Madagascar) using government aggregations of the annual total catch computed for national statistics.

3. Fitting several variants of generalized depletion models to weekly total catch, fishing effort and mean weight of octopus in the commercial catch for each year (2015 to 2020) separately, and selection of the best variant for each year in terms of numerical, statistical and biological criteria.

4. Deriving the instantaneous exploitation rate, the annually-aggregated exploitation rate, and escapement biomass in each annual season from the best generalized depletion model.

A detailed description on facts and constraints that led to the 4-stages methodological approach has been delivered in the first report with data up to 2016 [17].

When developing and curating a database of weekly catch, fishing effort, and sampled mean weight from 2015 to 2020, three BV's databases were used. These are named 'Master_Oct_OCT', 'Master_Tot_OCT' and 'Master_Cat_OCT'. In addition, regional annual total catch from 2015 to 2020 as communicated by government authorities, were also provided by BV (Table 1).

3.1 Weekly fisheries database from BV

An adequate database for the application of generalized depletion models contains three complete (no missing data) columns:

1. total catch in weight or numbers,
2. total fishing effort in any useful metric,
3. mean weight of individual fish or invertebrate in the catch from a sample of the catch or from the total catch,

all of these by rapid time step in a fishing season. The latter column is a columns of 1s whenever the catch is recorded in numbers while it is the mean weight of individual fish or invertebrates in the catch whenever the catch is recorded in weight. In the case of the present application the sample of the catch by BV is recorded both in weight and in numbers but as explained below the total catch by week has to be expanded three times to account for all removals, and in the last step the raising factor is calculated using national statistics for the SW Madagascar, which are recorded in weight. Therefore it was necessary to build the database for assessment using catch in weight.

The building of the three-columns database in the samples of fishing trips observed by BV was as follows:

1. Total catch in weight (kg) per week in BV's sample of fishing trips was calculated from the 'Master_Tot_OCT' database. This observed catch was the sum across days, villages, sous collector, company, data collector of the column named 'TotalOctopus' for each week of the season.
2. The fishing effort was measured as the number of fishers reporting catch in the sample of fishing trips recorded by BV in the 'Master_Oct_OCT' database. This database has a column called 'per_group' which enumerated, for each date and intermediary person aggregating the catch (column 'Sous.Collector'), the number of fishers from which the catch was aggregated. Thus fishing effort per week was evaluated as the sum of all daily numbers of fishers across the days and intermediaries in the week.
3. Finally, the mean weight in the catch per week was calculated by dividing the total catch in weight by the total catch in numbers across days of the week in 'Master_Tot_OCT' database.

Since this three-columns stock assessment database was built from BV's observed sample of fishing trips, it was necessary to expand the catch and the fishing effort columns to the region-wide total in order to build the corresponding three-columns database to the total number of fishing trips, both those in BV's sample and those not sampled by BV. This process involved three steps of expansion from sample to totals.

First, BV experts noted that there were a number of unsuccessful trips where the fisher went out to capture octopus and returned empty-handed (Table 1). These failed fishing trips are part of fishing effort and therefore should be included in the evaluation of total fishing effort per week, nevertheless they are not represented in the 'Master_Tot_OCT' and 'Master_Oct_OCT' databases. A third database, named 'Master_Cat_OCT', provided by BV did contain records of both, successful and failed fishing trips. From the data in that database I fitted a cubic spline to the weekly proportion of successful fishing trips to each year's data (Fig. 2). Having the weekly estimated proportion of successful fishing trips, fishing effort weekly values from BV's sampled fishing trips in the 'Master_Oct_OCT' database were augmented using:

$$f_{t,y} = \frac{\phi_{t,y}}{p_{t,y}}, p_{t,y} \sim Normal(\pi_{t,y}, \sigma_{t,y}) \tag{1}$$

where $f_{t,y}$ is the augmented weekly fishing effort, $\phi_{t,y}$ is the observed fishing effort, and $p_{t,y}$ is the estimated proportion of successful fishing trips, a random variable with a normal distribution with mean $\pi_{t,y}$ and standard deviation $\sigma_{t,y}$ for each week t and year y. This first step of expansion added a small amount of random error to the data to account for inaccuracies and imprecision due to sampling the proportion of successful fishing trips.

The second expansion step involved expanding the augmented fishing effort per week $f_{t,y}$ (which corresponded to the sample of fishing trips in 'Master_Oct_OCT' database augmented to include successful and unsuccessful fishing trips) in the 'Master_Oct_CAT' database, to the total catch by week recorded by BV in the 'Master_Oct_TOT' database. This expansion involved predicting the fishing effort in the sample of fishing trips in the 'Master_Oct_OCT' database to the total catch observed by BV in the 'Master_Oct_TOT' database using a linear regression predictor of the relation between catch in the 'Master_Oct_OCT' database and the corresponding augmented fishing effort.

Finally, the third expansion concerned both the catch and the effort per week from the total catch recorded by BV in the 'Master_Oct_TOT' database to the regional total of the entire SW Madagascar (Table 1). In this case, considering that the regional total for the SW region was a single number, the expansion of the weekly catch and fishing effort consisted of multiplying each weekly value by the raising factor calculated as the total annual catch in the Master_Oct_TOT database to the regional statistics total. This implies that the stock assessment will evaluate the stock for the entire region.

The database described in this subsection was compiled in the R system of statistical programming [18, 19]. The code used to built the stock assessment databases for each year from the three databases built by BV is available for continued use as new seasons are added to BV's databases.

Table 1: Global statistics of catch and fishing effort in BV database of fishing trips for octopus in SW Madagascar during the years covered by this stock assessment. Percentage of successful fishing trips (Success), annual sampled fishing effort and catch and annual regional total catch per year (from government records) are shown.

Year	**Success (%)**	**Sampled effort ((fishers' trips))**	**Sampled catch (kg)**	**Regional catch (kg)**
2015	66.5	8,933	264,871.3	649,909
2016	63.0	8,439	214,650.9	910,397
2017	64.2	6,464	163,669.0	837,133
2018	64.9	7,057	173,289.8	2,997,898
2019	70.9	8,640	145,828.1	5,235,241
2020	76.0	6,752	212,586.5	5,765,696

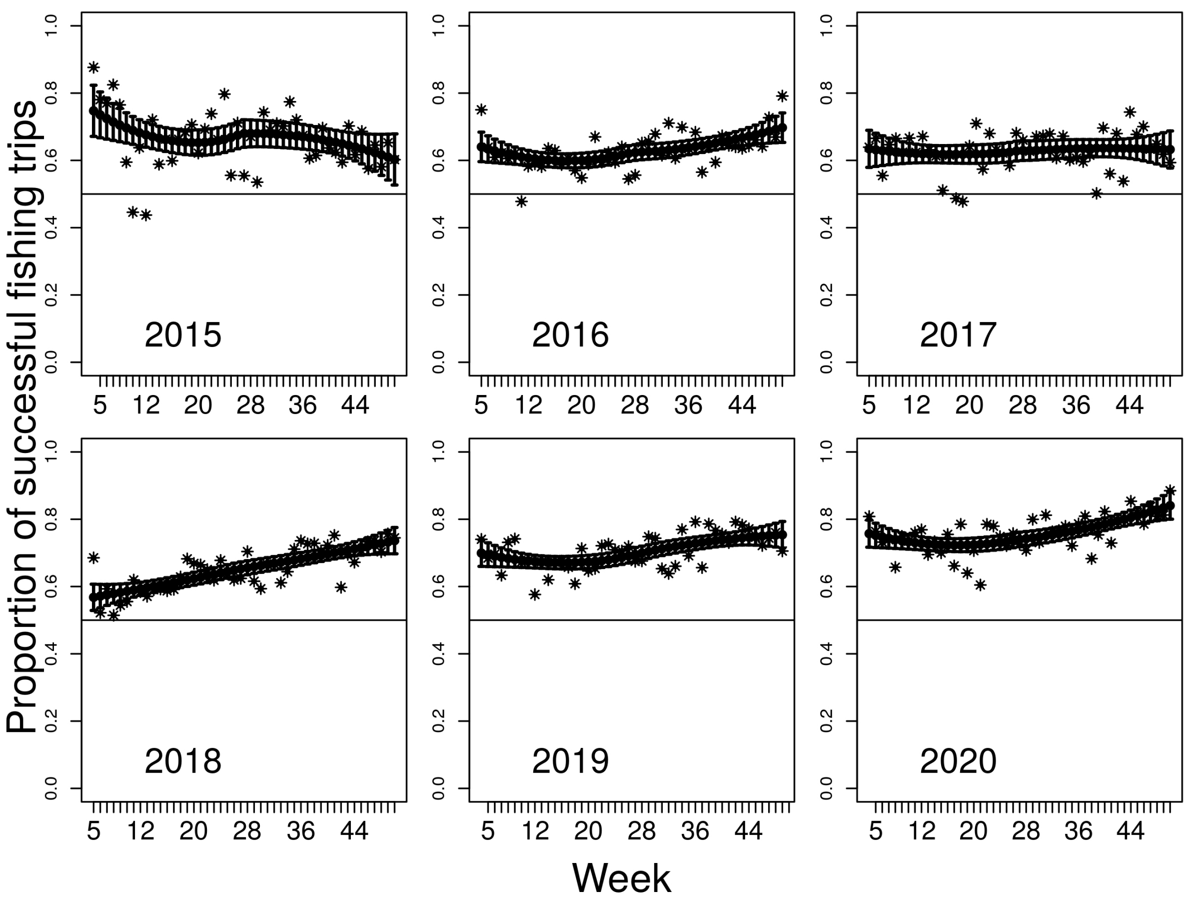


Figure 2: Proportion of successful fishing trips by week (asterisks) and estimated weekly trend (dots) Âą 2 standard deviations (bars) in BV's 'Master_Cat_OCT' database of fishing trips in the fishery for octopus in SW Madagascar

3.2 Generalized depletion models

The stock assessment methodology employed here has been described in several recent scientific articles [5, 6, 7, 8, 3, 9, 10, 11, 12, 13, 14, 15, 16]. Generalized depletion models running at daily or weekly time steps with data for a single season of fishing are called intra-annual generalized depletion (IAGD) models and have been applied to octopus [7], squid [16], sea urchins [14], and eel larvae [9, 11, 12] fisheries in recent scientific articles. These IAGD models evaluate the whole abundance in aggregated manner, i.e. including all cohorts present at any time as an aggregate of abundance. They have the general form:

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

where

- t is the time step (week),
- 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 fishers doing fishing trips,
- 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 week^{-1},
- m equals $e^{M/2}$,
- N_0 is the initial abundance, the abundance at the week before the first week in the effort and catch time series,
- i is an index that runs over previous time steps and up to the current time step (t),
- P are the magnitudes of pulses of abundance that enter the stock that can be fished by fishers,
- I is an indicator variables that evaluates to 0 before a specific pulse of abundance and to 1 during and after the pulse of abundance,

- p is the number of pulses of abundance that happen during a given season, happening at specific weeks each year, with j being the counter that runs from 1 to p, and
- τ is the specific week at which each pulse of abundance happens.

Parameters M, N_0, and the magnitudes of the pulses of abundance 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. 2. The true but un-observed catch at each week C is the product of the observed fishing effort E expended that week and the latent stock abundance that week, and this product is scaled by the scaling k. The model allows for zero catches in some weeks 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 and sufficient causes and the catch is the effect. In the second line of Eq. 2 the model is completed by using Pope's recursive expansion plus the effect of pulses of abundance 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 than the proportional increase in effort. 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 IAGD models, 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, as is in the present application) allows simultaneous estimation of N_0, M, k, the pulses of abundance P_j, α, and β. The timings τ_j of pulses of abundance are estimated by fitting models with varying configurations of τ_j and then selecting the configuration best supported by the data, for instance by selecting the timings τ_j that maximize the likelihood (when the likelihood model is comparable across model fits) and/or are best according to other criteria (see below). Good candidate values for the timings were determined by two techniques.

First, examination of the non-parametric catch spike statistic, defined as [15]

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

where χ is the observed catch. Highly positive values of this statistics in specific weeks suggest that at those weeks there have been pulses of abundance because the fishing effort was not high enough to explain the catch.

The second technique to discover weeks with pulses of abundance was fitting pure depletion IAGD models, models with no intra-season pulse of abundance, and then identifying the weeks with the largest positive residuals as candidate weeks for pulses of abundance.

The model in Eq. 2 describes the deterministic process that generates the true but un-observed catch under the model separately in each fishing season. The statistical framework is completed by taking the observed catch time series in the data as random variables whose mean time series is Eq. 2 with realized time series coming from any of a number of distributions. These distributions define the likelihood function that is to be maximized to estimate the parameters in the model. 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. Models with the Poisson distribution for the observed catch time series were also fitted. Likelihood formulas under the five distributional models are all listed in [10, Table 2].

Generalized depletion models were fitted using R package CatDyn, version 1.1-1 [19]. CatDyn depends on package optimx [20], 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. The combination of options for timing of those pulses, likelihood function, and numerical optimization routine led to fitting several alternative model variants for the effort and catch (in numbers) time series in each season. 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 any parameter were eliminated. This is a commonly employed criterion in stock assessment [21, 22, 23, 24]. Secondly, variants yielding unrealistic values of the natural mortality rate (i.e. less than 0.01 per week) given the known lifespan of the octopus, were also excluded whenever the set of variants included higher M estimates. 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 formula.

3.3 Management relevant derivations

Directly from results of fitting generalized depletion model, it is possible to calculate two measures of exploitation rate: instantaneous and annually aggregated. The instantaneous exploitation rate is weekly fishing mortality over weekly total mortality, fishing plus natural and the annually aggregated exploitation rate is the ratio of annual catch to stock biomass at some time during the season.

In CatDyn 1.1-1, weekly fishing mortality is calculated using Baranov's catch equation,

$$C_{t,f} = N_t \frac{F_{t,f}}{F_{t,f} + M}(1 - e^{-(F_{t,f}+M)t}) \tag{4}$$

and estimates of N_t, á¸ž and either the observed catch in numbers or the catch in numbers predicted by the depletion model. As the single unknown quantity at each time step in Baranov's catch equation, fishing mortality F_t is calculated using the *uniroot* R uni-variate solver. Some fishery management organizations such as the Food and Agriculture Organization (FAO) of the United Nations consider the instantaneous exploitation rate as a valid and useful biological reference point citing previous work by Patterson [25] showing that short-lived stocks maintain a stable and sustainable spawning biomass when the instantaneous exploitation rate is 40% or less.

Concerning the annually aggregated exploitation rate I used the stock biomass left at the end of each season (the escapement biomass) as the denominator in the calculation. Therefore the annually aggregated exploitation rate is interpreted as the fraction of the stock biomass at the end of the fishing season that was taken by the fishers during the season.

4 Results

4.1 Stock assessment database

Compilation of the three-columns stock assessment database as described in the previous section yielded very good catch-effort relationships in all fishing seasons (Fig. 3). The relationship appears close to linear in all years. This result also highlights that the raw data as collected by BV since 2015 (and less completely in earlier years [17]) in their three databases ('Master_Oct_OCT', 'Master_Tot_OCT' and 'Master_Cat_OCT') is of good quality and sufficient to conduct stock assessment with generalized depletion models.

Mean weight data shows that fishers started catching 1 kg octopus in the first few years but that they have started to catch smaller octopus in 2018, 2019 and 2020, averaging close to 800 g (Fig. 3). The mean weight data further shows relatively constant size across the weeks of the fishing season in all years, with no signs of a major pulse of recruitment from octopus that grow to the size hunted by fishers. This indicates that any pulses of abundance estimated with depletion models will either result from commercial size octopus migrating into the inter-tidal habitats hunted by fishers or new areas being explored and hunted by the fishers at specific times during the fishing season.

One implication of these interpretations of the constant trends in mean weight across the fishing seasons is that it is very likely that the octopus stock being hunted is not a complete, self-sufficient population but rather, a part of a major population that extends to deeper, sub-tidal waters.

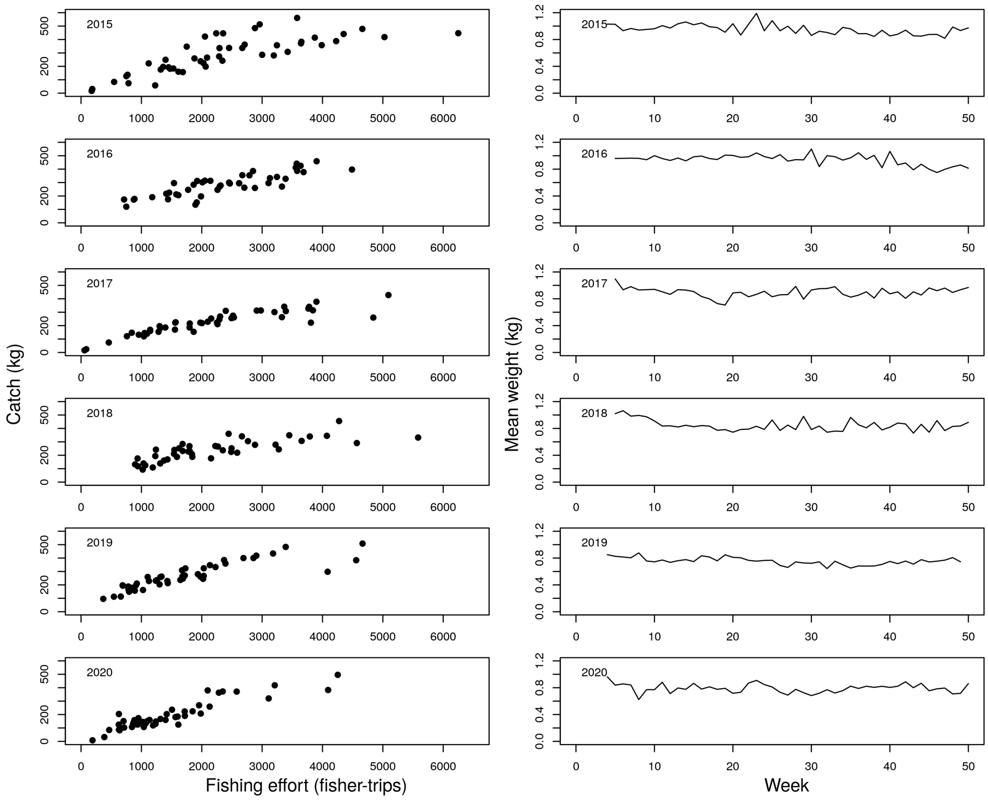


Figure 3: Weekly catch and effort relationship and mean weight of individual octopus in the fishery for octopus in SW Madagascar.

4.2 Generalized depletion models

Across the five seasons (2015 to 2020) a total of 320 model variants were submitted to maximum likelihood estimation. These differed on being fitted with any of five likelihood models (adjusted profile normal, adjusted profile lognormal, Poisson, exact normal and exact lognormal), any of two numerical optimization algorithms (*CG* and *spg*), and a few number of timing hypothesis (1 to 5 in-season pulses of abundance at different weeks). Most variants were fitted to the data from the 2016 season and a few dozen variants achieved successful numerical convergence in each of the five seasons (Table 2). Nevertheless, the short list of converged variants that yielded good numerical and statistical results usually amounted to just a few good fits. From this short list the best variant was selected for each season based on statistical and numerical criteria, namely low numerical gradients, small standard errors of estimates, and correlations between estimates close to 0. (Table 3).

Table 2: Number of fitted IAGD model variants for each season, number of converged variants, and short list of best variants.

Year	Total variants	Converged variants	Short list
2015	30	24	4
2016	150	105	45
2017	20	15	2
2018	30	11	4
2019	30	11	3
2020	60	26	4

Table 3: Characteristics of the best variant of IAGD model for each season. Object is the name is the name of the object containing optimization results in the software. Adj. prof. is adjusted profile. Method is the numerical optimization method. Timings is the weeks at which pulses of abundance were set.

Year	Variant	Object	Distribution	Method	Timings
2015	v18.15	madoct.sw.15.3P.apn.fit	Adj. prof. normal	CG	23,32,44
2016	v98.16	madoct.sw.16.4P.apln.fit	Adj. prof. lognormal	CG	5,23,29,35
2017	v07.17	madoct.sw.17.2P.1.apn.fit	Adj. prof. normal	CG	32,33
2018	v10.18	madoct.sw.18.3P.1.p.fit	Poisson	CG	23,24,25
2019	v19.19	madoct.sw.19.3P.1.apln.fit	Adj. prof. lognormal	CG	7,11,36
2020	v24.20	madoct.sw.20.5P.1.apln.fit	Adj. prof. lognormal	CG	5,8,12,37,45

The best variants for all seasons differed substantially in their configuration except for the numerical method used for optimization, with all best variants optimized using the *CG* method (Table 3). Adjusted profile normal, adjusted profile lognormal and Poisson distributional models were selected as best and a minimum of 2 and a maximum of 5 pulses of abundance were estimated in the weekly catch dynamics (Table 3). These best variants also had relatively good correlation structures with the best correlations in the 2015 and 2020 seasons, though in the other seasons at least half of pairwise correlations are less than 0.25 in absolute value (Fig. 4).

The timings of abundance pulses does not follow a pattern season to season, except that nearly all seasons have at least one pulse at mid-season, between the 29th and 37th week (Table 3). There could be early pulses (2016, 2019 and 2020) and late pulses as well (2015 and 2020). This absence of pattern means that those pulses are either expansions of the fishing grounds by fishers hunting in new areas or episodic migrations of octopus from sub-tidal depths.

The fit of IAGD models to the data of each season are shown in Figs, 5, 6, 7, 8, 9 and 10). All models show good fit the the data and adequate residuals diagnostics, with few outlying residuals points and a few quantiles out of the diagonal in the quantile-quantile plots in seasons 2016, 2018 and 2020.

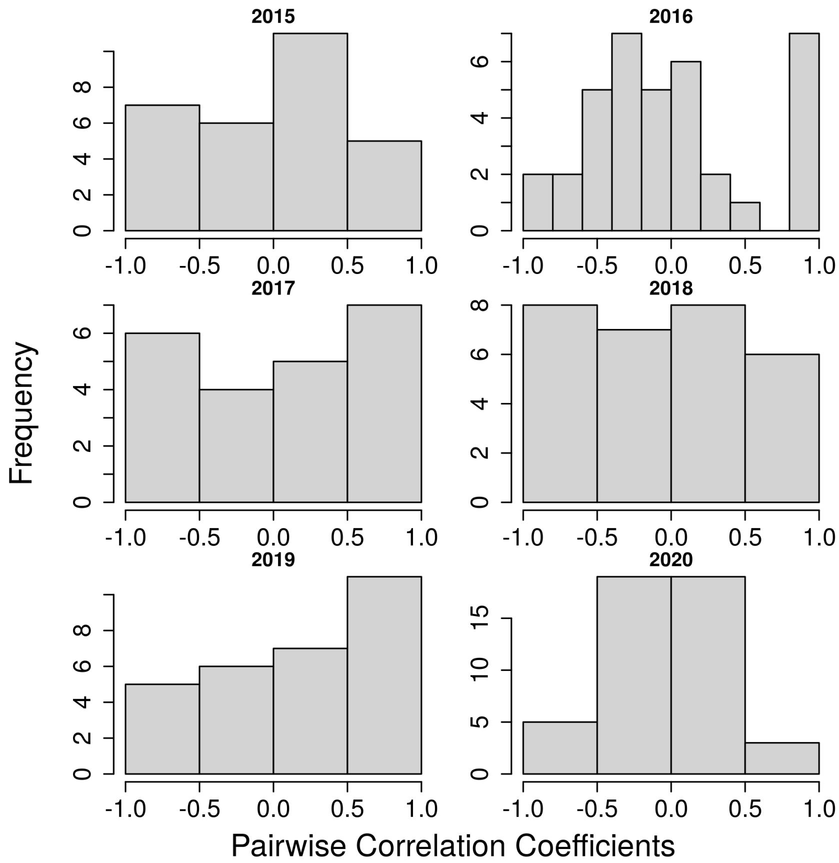


Figure 4: Correlation structure of best IAGD model variants for each of the six fishing seasons.

Parameters directly estimated by the best IAGD models are presented in Tables 4, 5, 6, 7, 8 and 9. These parameters can be classified in two groups. Natural mortality (M), initial abundance (N_0) and the pulses of abundance are stock abundance parameters, while scaling (k), effort response (α) and abundance response (β) are fishing operational parameters.

Concerning stock abundance parameters, the best models fitted to the 2018 and 2020 seasons did not provide reliable estimates of natural mortality (M), though in the other seasons natural mortality was estimated with fairly good statistical precision. In these seasons, natural mortality ranged from 0.0127 week^{-1} (0.6731 year^{-1}) to 0.0498 week^{-1} (2.6394 year^{-1}), a four-fold wide range. At the start of the season there are typically a few million octopus, and pulses of abundance add from a few hundred to a few million more octopus. The larger pulses are estimated with good precision.

With regards to fishing operational parameters, they are typically estimated with good precision (except the scaling in 2018) although in some seasons the measures of statistical precision could not be computed during optimization. Scaling ranges from the order of 10^{-5} to 10^{-9} but this variation seems to be caused by large fluctuations in stock abundance rather than on changing fishing practices. The effort response is either proportional (close to 1) or synergistic (2016, 2017 and 2019) while the abundance response is mostly hyperstable.

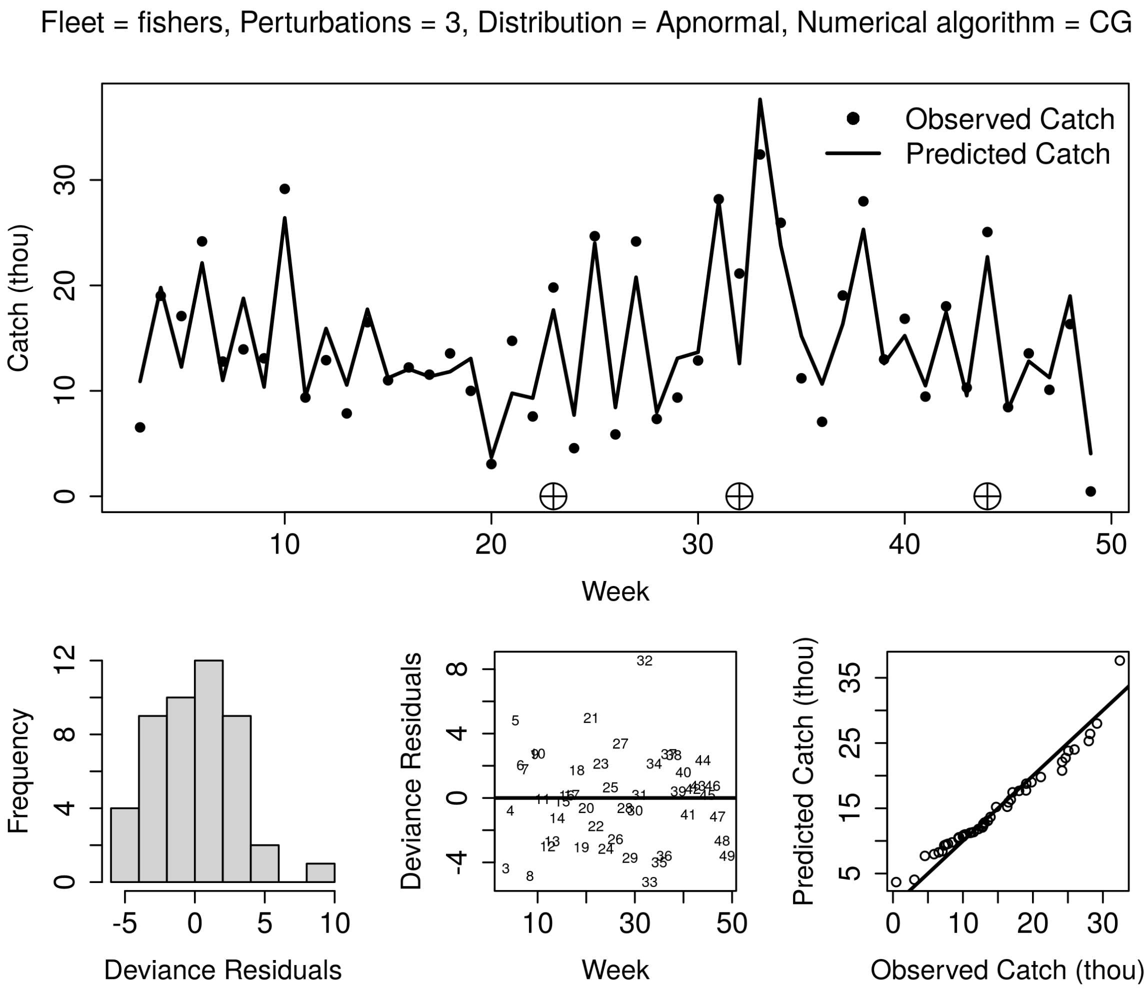
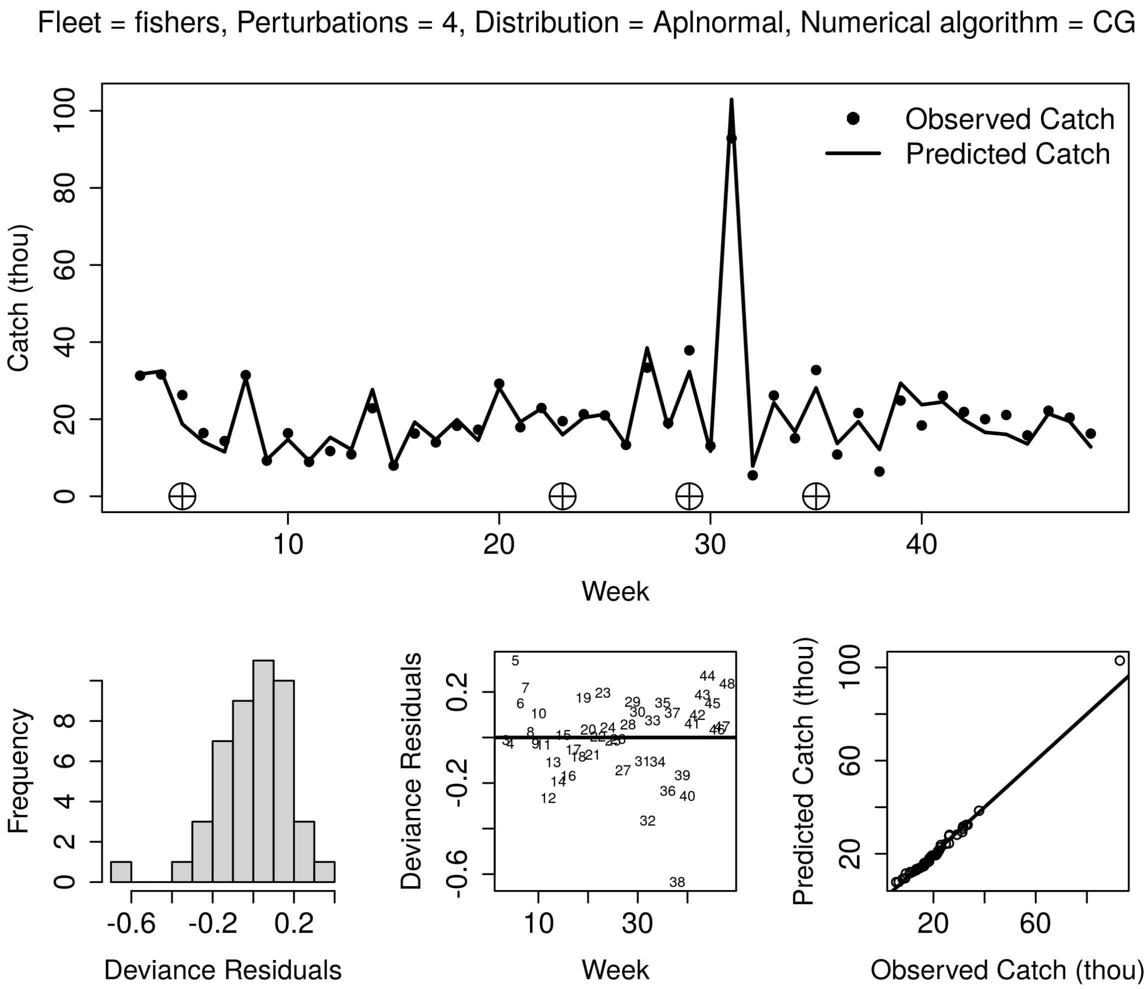


Figure 5: Fit of the best IAGD variant to the data from the 2015 season. Top panel: Catch in numbers data (dots), prediction of catch in numbers data by the IAGD variant (line), timing of abundance pulses (target sign), and total catch and the biomass left at the end of the season (escapement biomass). Bottom panels: diagnostics plots based on deviance residuals and quantiles. Left: residuals histogram. Center: residual cloud. Right: observed versus predicted catch quantiles.



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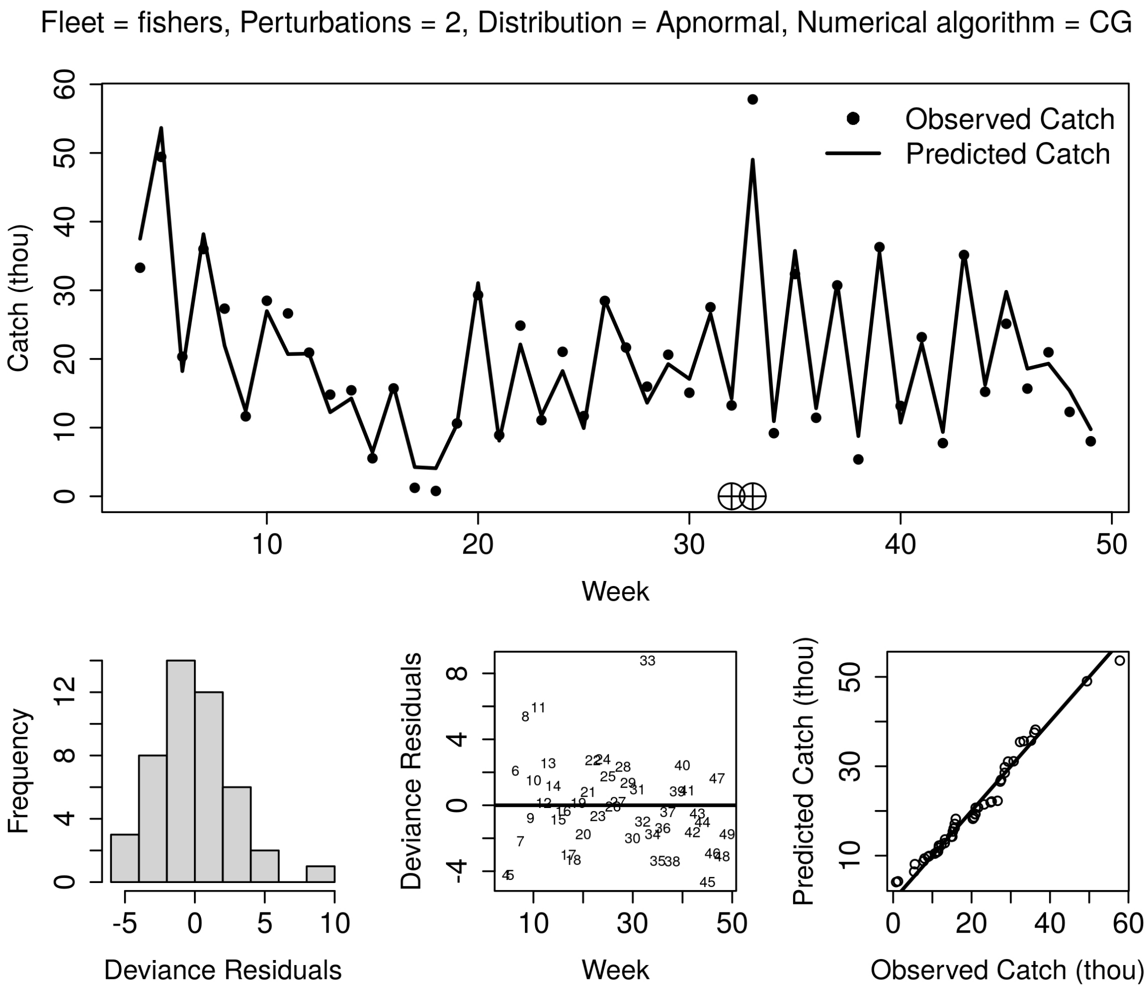

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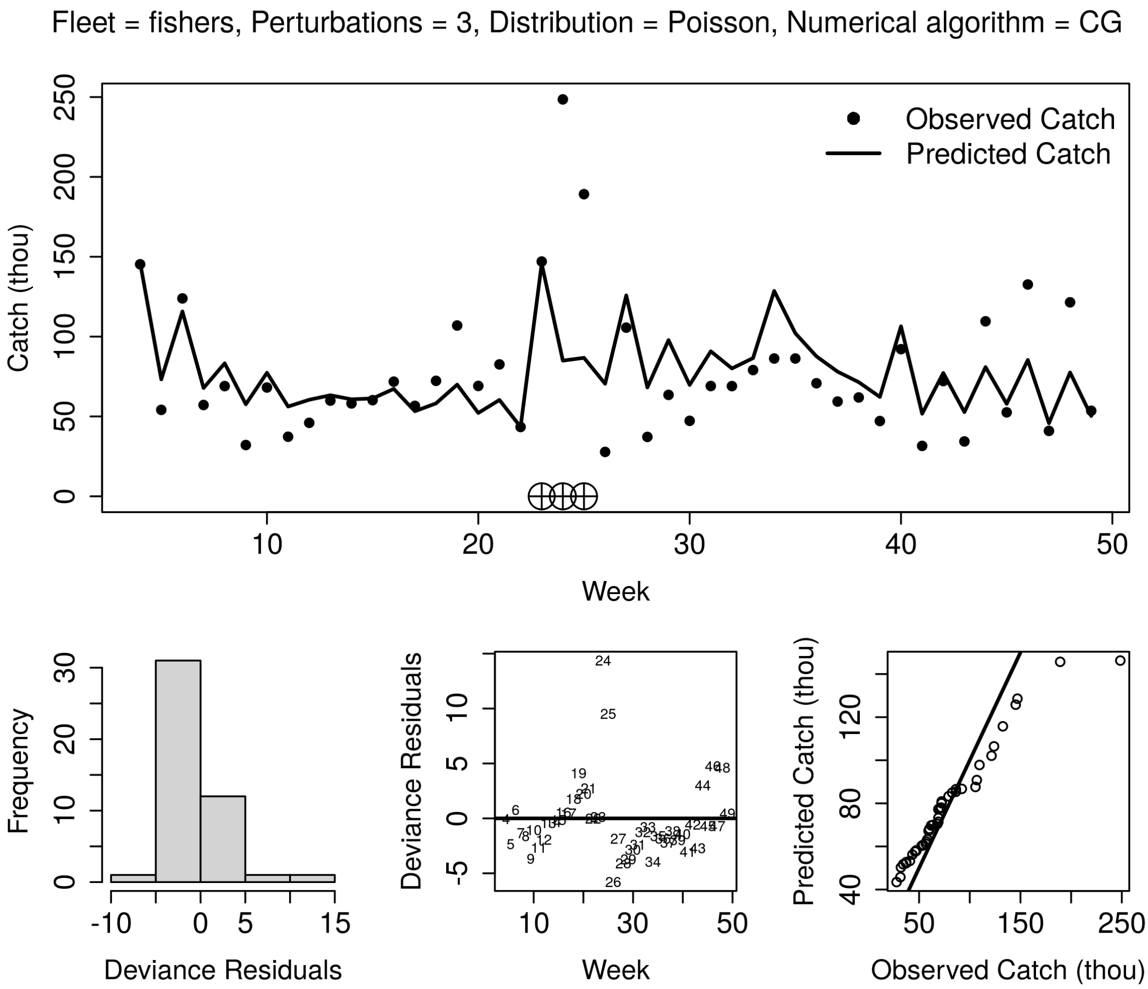

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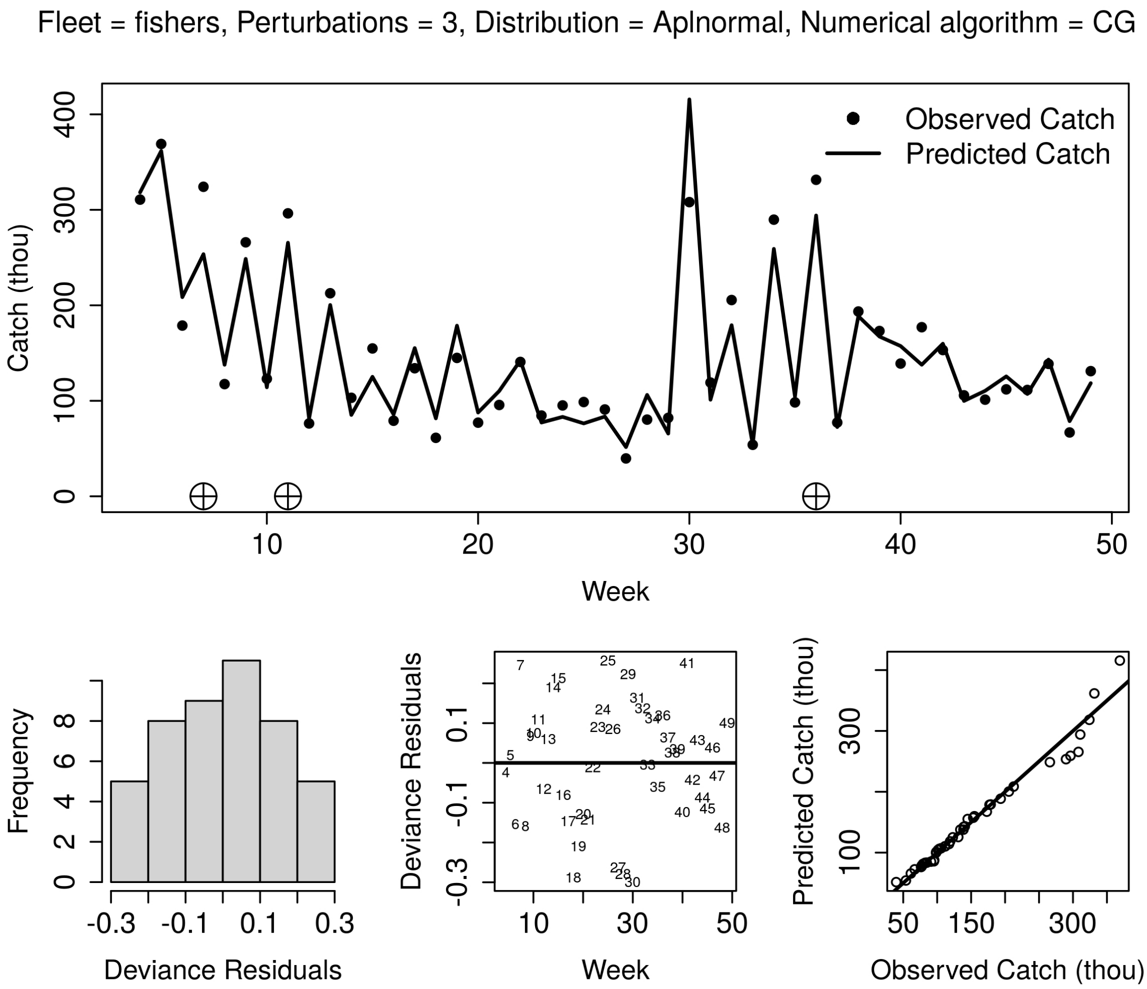

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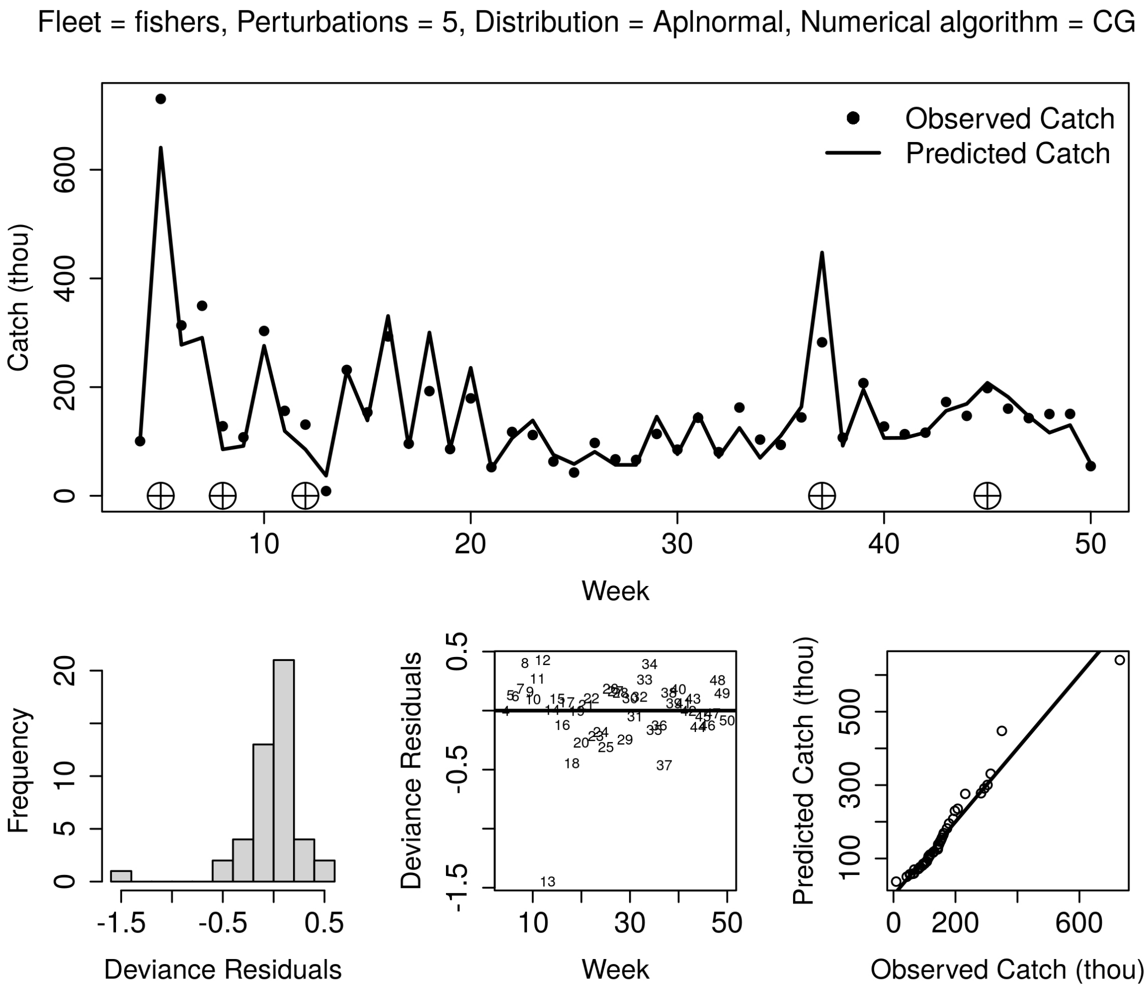

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Table 4: Directly estimated parameters of the best IAGD model fitted to the data from the 2015 season. MLE: maximum likelihood estimate. CV: coefficient of variation. CVs not shown correspond to failures to estimate standard errors.

Parameter	**Week**	**MLE**	**CV** (%)
M (week^{-1})		0.0226	29.4
N_0 (thousand)		1,862	5.2
Abundance pulse 1 (thousand)	23	1,060	23.1
Abundance pulse 2 (thousand)	32	386	44.0
Abundance pulse 3 (thousand)	44	200	92.9
k (1/fishers)		0.00004099	0.8
α		1.0923	3.9
β		0.7704	6.7

Table 5: Directly estimated parameters of the best IAGD model fitted to the data from the 2016 season. MLE: maximum likelihood estimate. CV: coefficient of variation. CVs not shown correspond to to failures to estimate standard errors.

Parameter	**Week**	**MLE**	**CV** (%)
M (week^{-1})		0.0498	47.3
N_0 (thousand)		5,213	70.7
Abundance pulse 1 (thousand)	5	1,244	268.1
Abundance pulse 2 (thousand)	23	3,122	6.8
Abundance pulse 3 (thousand)	29	112	651.1
Abundance pulse 3 (thousand)	35	2,110	66.0
k (1/fishers)		0.0000005863	0.4
α		2.1098	
β		0.2853	

Table 6: Directly estimated parameters of the best IAGD model fitted to the data from the 2017 season. MLE: maximum likelihood estimate. CV: coefficient of variation. CVs not shown correspond to to failures to estimate standard errors.

Parameter	**Week**	**MLE**	**CV** (%)
M (week^{-1})		0.0127	81.8
N_0 (thousand)		6,888	40.4
Abundance pulse 1 (thousand)	32	725	
Abundance pulse 2 (thousand)	33	3947	
k (1/fishers)		0.00004542	2.9
α		1.5899	0.3
β		0.2062	4.0

Table 7: Directly estimated parameters of the best IAGD model fitted to the data from the 2018 season. MLE: maximum likelihood estimate. CV: coefficient of variation. CVs not shown correspond to to failures to estimate standard errors.

Parameter	**Week**	**MLE**	**CV** (%)
M (week^{-1})		0.0002247	247.0
N_0 (thousand)		5,402	23.5
Abundance pulse 1 (thousand)	23	203	237.5
Abundance pulse 2 (thousand)	24	2,167	28.8
Abundance pulse 3 (thousand)	25	85	401.0
k (1/fishers)		0.0000001558	369.7
α		0.9412	7.3
β		1.4285	27.5

Table 8: Directly estimated parameters of the best IAGD model fitted to the data from the 2019 season. MLE: maximum likelihood estimate. CV: coefficient of variation. CVs not shown correspond to to failures to estimate standard errors.

Parameter	**Week**	**MLE**	**CV** (%)
M (week^{-1})		0.01376	131.8
N_0 (thousand)		2,371	46.9
Abundance pulse 1 (thousand)	7	3,419	49.4
Abundance pulse 2 (thousand)	11	3,313	67.2
Abundance pulse 3 (thousand)	36	2,945	50.6
k (1/fishers)		0.0000008786	3.8
α		1.7815	0.3
β		0.3111	3.9

Table 9: Directly estimated parameters of the best IAGD model fitted to the data from the 2020 season. MLE: maximum likelihood estimate. CV: coefficient of variation. CVs not shown correspond to to failures to estimate standard errors.

Parameter	**Week**	**MLE**	**CV** (%)
M (week^{-1})		0.0001504	998.7
N_0 (thousand)		7,333	4.9
Abundance pulse 1 (thousand)	5	4,803	13.7
Abundance pulse 2 (thousand)	8	13	1410.4
Abundance pulse 3 (thousand)	12	3	1387.3
Abundance pulse 4 (thousand)	37	2,706	28.5
Abundance pulse 5 (thousand)	45	2,851	37.9
k (1/fishers)		0.00000001046	4.2
α		1.1614	
β		1.4867	1.0

4.3 Management relevant derivations

In the 2015, 2016, and 2017 seasons, fishing mortality per week was under natural mortality (Fig. 11) while in season 2019 it was over natural mortality, and highly so at the start of the season. As explained earlier (Tables 7 and 9), the natural mortality rate could not be adequately estimated with the data from the 2018 and 2020 fishing seasons.

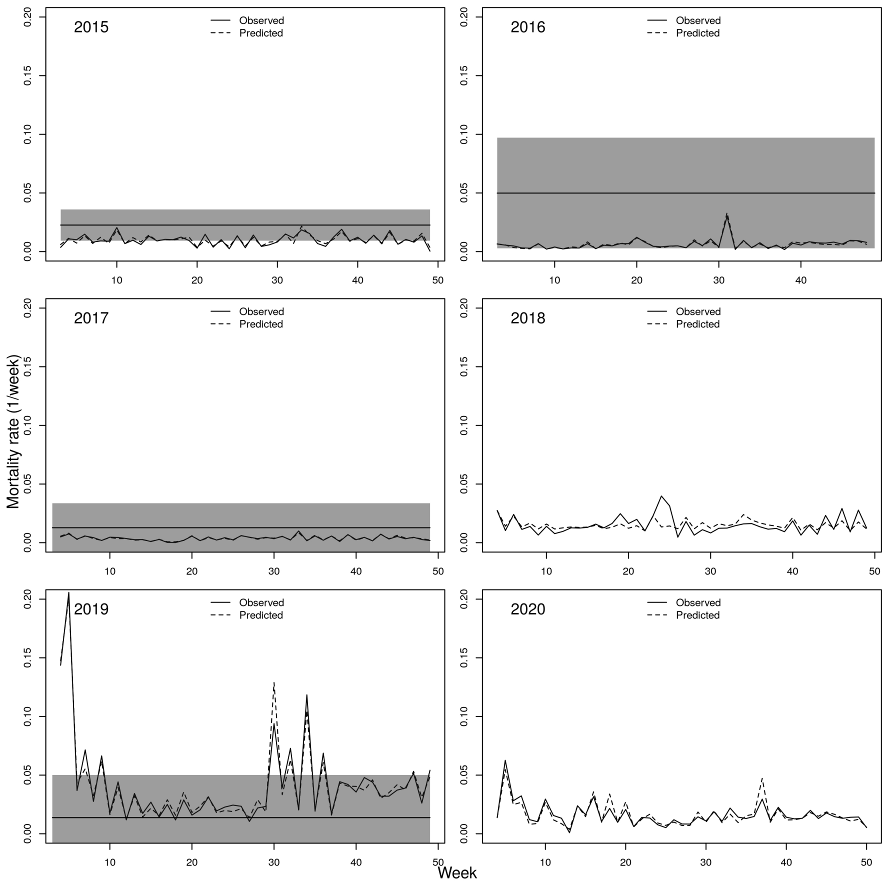

Figure 11: Fishing mortality versus natural mortality (horizontal line) ± 2 standard errors (grey band). The observed fishing mortality is computed with Baranov's equation and the observed catch while the predicted fishing mortality is computed with the catch predicted by the model.

Figure 12 summarizes management relevant quantities that can be used as biological reference points from results of IAGD models. Catch tracks changes in biomass except in 2017 and 2019. It seems that the stock has been changing widely in abundance, from a low escapement biomass of 340 tonnes in 2019 to a high of 9000 tonnes in 2020. The annually aggregated exploitation rate has been quite intense over the time series, usually staying close to 50%, reaching much higher in 2019, when this exploitation rate exceeded 300%. Recall that this exploitation rate is the fraction of the escapement biomass that was taken as catch. In 2019 the catch was 3-times higher than the escapement biomass. The instantaneous exploitation rate, for which an upper bound of sustainable exploitation applicable to short-lived stocks have been determined at 40% [25], was higher than that upper bound in 2015 and most remarkably in 2019. Recall that the best IAGD models did not produce a reliable estimate of the natural mortality rate from the fishing in 2018 and 2020 so the instantaneous exploitation rate cannot be determined for those years. Nevertheless, considering the escapement biomass and the annual catch as well as the annually aggregated exploitation rate, the fishing was probably over the upper bound of 40% in 2018 and 2020, although perhaps not as much as in 2019.

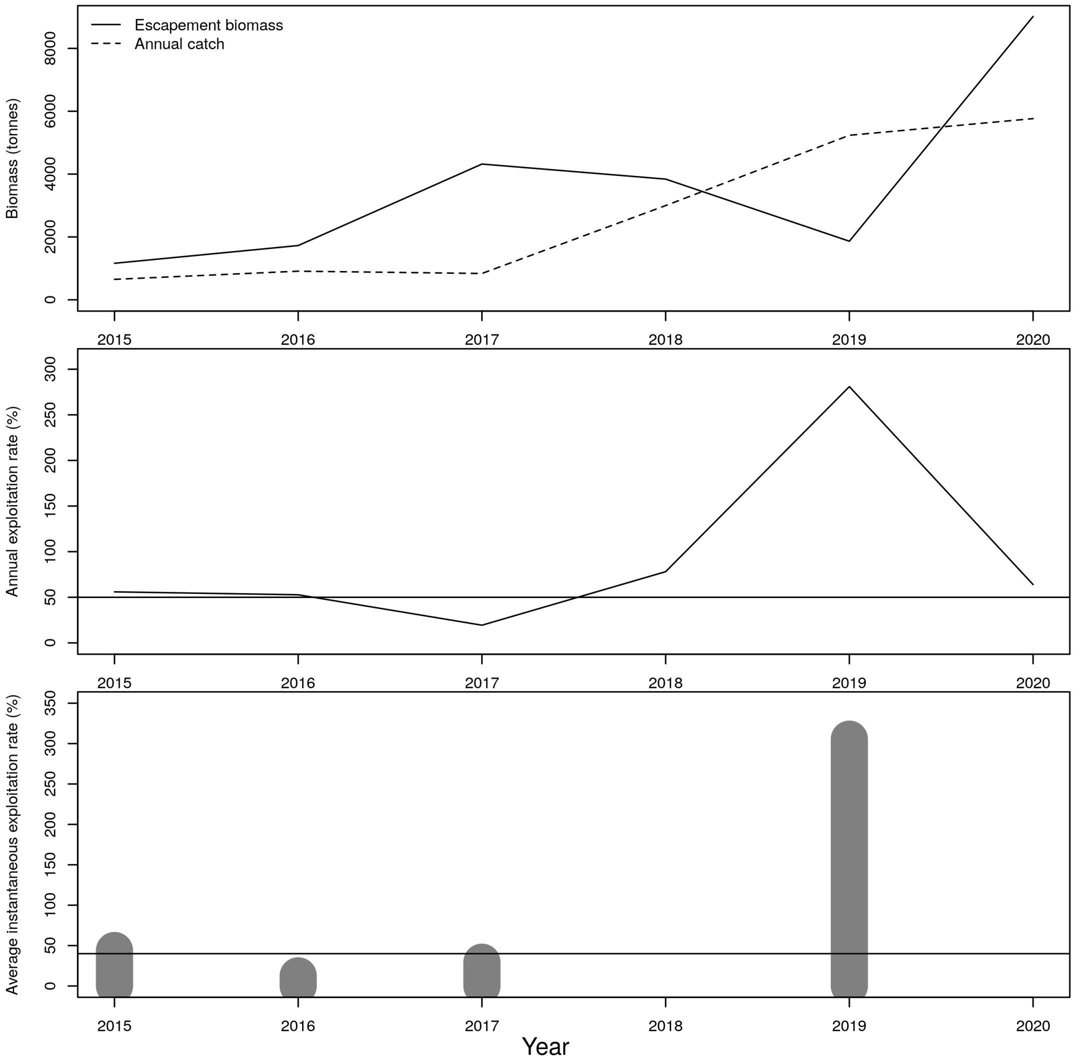

Figure 12: Top panel: escapement biomass (left at end of season) and annual catch. Center panel: annually aggregated exploitation rate (annual catch as percentage of escapement biomass. Bottom panel: average instantaneous exploitation rate (annual mean of the weekly ratio M/(F+M) as percentage).

5 Discussion

The databases being built by BV have proven useful to determine the octopus stock status in SW Madagascar with intra-annual generalized depletion (IAGD) models. The database covers now six years and it comprises a substantial percentage of the regional catch as communicated by authorities. The lowest percentages of total regional catch recorded in BV databases were 3% (2019), 4% (2020) and 6% (2018) and the largest percentage was 41% (2015). At those sample sizes, the databases compiled by BV could be considered as representative of the complete fishery though it is noteworthy that the years of the highest catch (2018, 2019 and 2020), when BV databases covered less of the complete fishery, IAGD models have more difficulty during likelihood optimization leading to inability to estimate the natural mortality rate and consequently, the instantaneous exploitation rate, with the exception of 2019. If it were possible, it would be advantageous to scale up the observations of fishing trips when a season starts to show signs that it will produce large catches.

The stock was fished at sustainable rates, although very close to maximum capacity, up to 2017. Starting in 2018 and especially in 2019, there was a substantial increase in the intensity of fishing, leading to clearly excessive rates in 2019. Nevertheless, although it was not possible to estimate exploitation rates in 2020, it was possible to estimate escapement biomass and it was a very high estimate. This shows that the stock is highly resilient, capable of quick rebuilding of biomass. Previous research in octopus fisheries [7] shows that under pressure from fishing, life history parameters lead to population dynamics dominated by cycles of abundance, with high abundance years followed by low abundance years. Under such dynamics, excessive exploitation rates may lead the stock to collapse in years of low biomass in the cycle. In this case, the top and mid panels of Fig. 12 suggest that the stock may indeed be entering a cycle of fluctuations in abundance. These cycles ultimately originate in a highly unstable relationship between spawners in one year and recruitment in the next year [7], with the fishing acting as the trigger to unleash a period of biomass fluctuations, since fishing plays the role of a disturbance acting upon an unstable equilibrium. If this is the dynamics that the stock of octopus in South-West Madagascar is entering, it would be necessary to reduce exploitation rates so that total annual catches are always under the lower point of biomass fluctuations.

Fishers are roughly leaving the same biomass in the sea at the end of each season as the biomass that they take during the season. This level of removals is usually borderline when viewed from the perspective of sustainability. A further observation is that the rate of depletion due to fishing was close to the 40% level of the rate of depletion due to natural causes up to 2017 and increased substantially in 2019. These highlights indicate that the fishery is likely working at full capacity or exceeding full capacity (from 2018) and that therefore there is no room for growth in fishing effort, which in this study is measured as the number of fishers carrying out fishing trips per week.

In other octopus fisheries [3, 7], IAGD models usually discover periods of recruitment to the vulnerable stock (octopus that grow to the sizes hunted and retained by fishers) and periods of spawners emigration out of the vulnerable stock. In this application the pulses of abundance were irregularly distributed across the season thus precluding their interpretation as recruitment pulses of young octopus growing to commercial size. Furthermore, the progression of mean weight across the season does not reveal any regular time of the year when octopus size in the catch drops. Moreover, there was no clear evidence of any drop in catch that could indicate a period of spawners emigration. This lack of pattern in the timing of abundance pulses and lack of evidence for emigration pulses suggest that the stock being fished is part of a larger stock and therefore population level phenomena are not well observed during the fishing. Alternatively, the stock being fished is a complete population unit but recruitment occurs continuously thus precluding the observation of patterns in the timings of abundance pulses. Considering the known biology of cephalopods, which includes a main period of mating and complex population structure with identifiable cohorts [26], it seems that the hypothesis of continuous recruitment during the fishing season is less likely than the hypothesis that the stock being fished is part of larger population unit. The fact that fishing happens mostly in the intertidal zone further indicates that the stock being fished is part of a larger stock that extends to deeper waters at subtidal depths, thus explaining the lack of pattern in the timings of recruitment pulses.

Spawners' emigration pulses can be observed in the intra-season catch time series when the method of fishing uses bait, since spawning females stop feeding [7]. In the present case the method of fishing may make observing spawners emigration pulses difficult due to fishers possibly hunting for females that are attending to their broods. One option to resolve these questions is a better understanding of fisher's behavior. Do they catch females that are in their dens caring for their broods? Better knowledge of fishers' patterns of use of fishing grounds may also help clarifying the nature of the pulses of abundance, for instance by pointing out to fishing switching to new areas at certain times during the season, which may coincide with the observed pulses of abundance in IAGD models. If such coincidence do exist then the pulses of abundance are additions of new areas to the fishing grounds.

Further clarification of whether the catch dynamics as observed from fishing in the intertidal zone may capture population processes could be obtained by conducting simple biological studies. For instance, is there a clear progression of sexual maturation during the fishing season? Do mating happens in the intertidal zone contemporaneously with the fishing season? These questions are scientific in nature but they are key to understand whether it is possible to derive biological references points from the population dynamics of the stock, such as those obtained from surplus production models. The determination of biological reference points connected to the capacity of the stock to renew itself depends on having the fishing happening over a complete population unit. Meanwhile, the tools demonstrated here as stock assessment models and biological reference points connected to exploitation rates are useful to determine levels of fishing effort that will maintain a sustainable activity. Population-dynamics biological reference points such as quotas that protect the spawning biomass will have to wait until the time series of data grows to ten or more years.

6 Conclusions

1. The databases built by BV from 2015 to 2020 are useful for stock assessment purposes with intra-annual generalized depletion models.

2. The absence of pattern in the timings of abundance pulses as well as the lack of evidence of spawners' emigration pulses suggest that the stock being fished is part of a major population unit that extends to subtidal depths.

3. Stock biomass amounts to a few thousand tonnes and it appears to have started to fluctuate in the last three years.

4. The annual catch tracks well changes in biomass, with largest biomass and catch observed in the latest year (2020).

5. The fishing has been conducted mostly with sustainable exploitation rates over the period of 2015 to 2017 and it appears to be currently operating above maximum capacity.

7 Management Advice

This management advice is exclusively in relation to the biological condition of the stock 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. It is necessary to scale up the observation of fishing trips by BV enumerators because the total annual catch has been increasing substantially since 2018 and currently the coverage of the catch observed by BV enumerators is just 3-6% of the official totals.

2. Continue growing the three databases recording the same variables that are recorded currently.

3. Create a fourth database of biological characteristics such as sex, mantle length, and reproductive condition, by sampling a low percentage of fishing trips, to better understand the population dynamics of the stock.

4. Continue application of intra-annual generalized depletion models to derive exploitation-rate connected biological reference points.

5. Do not allow any significant increase in fishing effort because the current levels already appear capable of exerting excessive mortality rates in the most recent seasons.

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