Développement d'un modèle stochastique de surproduction en vue de gérer les captures accidentelles d'espèces protégées

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Résumé. La gestion des prises accidentelles d'espèces protégées dans les engins de pêche est un enjeu majeur pour atteindre les objectifs de la Stratégie de l'Union Européenne en faveur de la biodiversité à horizon 2030. Les statistiques des prélèvements réalisés ne sont, en général, pas fiables car non-systématiques, ou issues déchantillons non-représentatifs. Les données de prélèvements concernant les espèces protégées sont donc très parcellaires et biaisées, ce qui complique l'évaluation de la soutenabilité des activités humaines. Toutes les espèces de cétacés sont protégées au niveau national et européen ; néanmoins celles-ci sont aussi impactées par les captures accidentelles. C'est le cas du dauphin commun (*Delphinus delphis*) dans le Golfe de Gascogne, dont les manquements en matière de protection valent aujourd'hui à la France une mise en demeure de la Commission Européenne et à l'Etat un arrêté de fermeture des pêcheries à risque pendant un mois durant l'hiver 2024 ordonnée par le Conseil d'Etat.

Un outil important pour gérer les impacts des pêcheries est le calcul de points de référence limites, aussi appelé seuils de prélèvements au-delà desquels la viabilité à long terme des populations impactées n'est plus garantie. Le calcul de tels seuils repose sur une méthodologie mise en place par la Commission Baleinière Internationale (CBI) au cours des années 1990 et qui reposent sur la simulation numérique de populations virtuelles soumises à des prélèvements dont l'ampleur est déterminée par une règle de gestion. Ces règles de gestion pour calculer les seuils sont évaluées dans un panel de scénarios pour évaluer la robustesse de ceux-ci à divers cas de figures dont des biais dans les données (sous-estimation des prélèvements par sous-déclaration, etc.). Deux règles sont actuellement utilisées : le PBR ("Potentiel Biological Removal") tel que défini dans la loi états-unienne sur la protection des mammifères marins ; et le RLA ("Removals Limit Algorithm") inspiré des travaux de la CBI.

Nous avons développé un modèle stochastique dit de ”sur-production”, modèle couramment utilisé en halieutique pour calculer des points de références ou des quotas pour des espèces exploitées. Ce modèle paramétrique reste simple (4 paramètres à estimer) et est informé par les prélèvements et l'abondance estimées d'une espèce pour calculer un taux de prélèvement (en pourcentage de l'abondance) compatible avec la viabilité à long-terme d'une population. Néanmoins, il fait une hypothèse restrictive de stationnarité des prélèvements qui n'est pas réaliste : la gestion doit précisément amener à des taux non-stationnaires puisqu'un objectif de restauration de la biodiversité est de minimiser au cours de temps les captures accidentelles. Nous proposons une approche de vraisemblance pondérée pour s'accommoder de cette non-stationnarité. Au travers d'une étude de simulations, nous montrons comment notre modèle conduit à une règle de gestion compatible avec les ambitions actuelles de conservation, notamment celle de minimiser l'impact des activités humaines sur les espèces protégées, dauphins inclus.

Mots-clés. évaluation de stratégie de gestion, `Stan`, captures accidentelles, cétacés, Bayesien

Abstract. Managing human activities, which can result in additional mortality on many marine Protected, Endangered or Threatened Species (PETS) is key to reach the ambitious set out by the EU 2030 Biodiversity Strategy. By-catch, the undesirable and non-intentional catch of non-target species in marine fisheries, is one of the main causes of mortality of marine mammals (which are often PETS) worldwide. Data on anthropogenic removals (including by-catch) of PETS (including marine mammals) are often unreliable because of, among others, inadequate sampling design, lack of enforcement, non-representative samples and underreporting (due for example to social desirability bias). All cetacean species benefit from some legal protection whether at the national or international level. The common dolphin (*Delphinus delphis*) in the Bay of Biscay epitomized the current challenges : the failure to enforce its strict protection earned (i) France an infringement procedure from the European Commission ; and (ii) the French Government the ordnance from the highest administrative court ('The Conseil d'Etat') of a one month spatio-temporal closure of all high-risk fisheries operating in the Bay of Biscay in the winter 2024.

Managing by-catch hinges on the computation of so-called biological reference points, also known as removals limits/thresholds : these represent an upper limit to the number of animals that can be removed from a population without compromising the long-term viability of said population with unacceptably high probability. Methods to compute removals limits for cetaceans originate from scientific work carried out in the 1990s by the International Whaling Commission (IWC) whereby computer simulations are harnessed to investigate the likelihood outcomes of different management schemes. The framework outlined by the IWC used so-called 'harvest control rule' (or just control rule) that take data from current monitoring as inputs to output a threshold (or a quota in case of a commercial species). Importantly, the framework allows to assess the effect of knowledge gaps and data biases to devise control rules that are robust against these. Two rules are commonly in use : the Potential Biological Removal (PBR) from the US Marine Mammal Protection Act ; and the Removals Limit Algo-

rithm, a child of the Catch Limit Algorithm devised to set quotas on the hunt of large whales.

We developed a stochastic surplus production model, a kind of parameter-lean model common in fishery sciences, and proposed a new control rule derived from this 4-parameters model. The model assumes (i) a simple proportional relationship between true abundance and removals, and (ii) stationarity (time-invariance) in removal rate. This assumption is untenable if management is to be effective as the very purpose managing anthropogenic removals of PETS is to minimize them. To preserve parameter-leaness, we resorted to a weighted-likehood approach for estimation (in a Bayesian framework) with time-dependent weights chosen such that older removal data are progressively and smoothly down-weighted. Using simulations, we benchmarked our new control rule relying on the stochastic surplus production model in a case study which revealed the competitiveness of the new rule to meet current conservation policy desiderata such as minimizing removals over time.

Keywords. management strategy evaluation, `Stan`, by-catch, cetaceans, Bayesian

1 Texte long

Introduction

Human activities in the oceans are increasing and can result in additional mortality on many marine Protected, Endangered or Threatened Species (PETS). By-catch, the undesirable and non-intentional catch of non-target species in marine fisheries, is one of the main causes of mortality of marine mammals (which are often PETS) worldwide. When quantitative conservation objectives and management goals are clearly defined, computer-based procedures can be used to explore likely population dynamics under different management scenarios and estimate the levels of anthropogenic removals, including by-catch, that marine mammal populations may withstand. Two control rules for setting removals limits are the Potential Biological Removal (PBR; Wade 1998) established under the US Marine Mammal Protection Act and the Removals Limit Algorithm (RLA; Cooke 1999) inspired from the Catch Limit Algorithm developed under the Revised Management Procedure of the International Whaling Commission (IWC). Both rules were tested and developped in procedures originally labeled 'simulation trials' and nowadays called Management Strategy Evaluations (MSE).

A management strategy is an agreed-upon set of rules for determining thresholds beyond which a conservation objective runs the risk of not being met with unacceptably high probability. This strategy defines management objectives in the form of thresholds that managers can monitor from available data, with the management objectives that these thresholds are not exceeded. MSE needs generative models that can generate (synthetic) data that are similar to observed, and crucially, currently available data. These models need to be more than simple curve-fitting devices and should be infused with ecological realism to reproduce and simulate the dynamics of an ecological system such as a population subjected to anthropogenic removals on top of natural processes (*e.g.* density dependence). Scientists can then evaluate the performance of management actions in 'what-if', or counterfactual, scenarios to set efficient management objectives. Importantly, the latter will be gauged against observable and available data (*e.g.* abundance and by-catch estimates, along with their uncertainties) only and not from unknown quantities (*e.g.* true abundance). Uncertainties in the underlying model and potential biases and uncertainty in the observed data must be considered in order to ensure robust management.

MSE requires in practice several components, including:
(1) one or several unambiguous quantitative conservation objective;
(2) a data simulator (or operating model) to emulate population dynamics and the effects of anthropogenic activities on this population;
(3) a control rule, whose computation accounts for the expected quantity and quality of observable data; to set a removals limit beyond which the impact of human activities runs the risk of failing the conservation objective(s) in (1); and
(4) performance metrics, necessarily context-dependent and policy-relevant, reflecting the trade-off between the potentially many conservation objectives defined previously.
For each management strategy, population dynamics are simulated, human activities have impacts, a control rule is applied: performance metrics are monitored and ultimately assessed

with respect to the conservation objective. Items (1) and (4) should be agreed upon by all stakeholders or taken from national or international law. Items (2) and (3) are under the remit of scientists, whose task is to test a large panel of realistic scenarios to buffer the management strategy against uncertainties and potential biases in the available data. MSE is computer intensive and needs tuning via simulations. Running a large number of simulations has become mundane yet coding an adequate data simulator may present a daunting task. To minimize duplication of effort and to enhance reproducibility we wrote the `RLA` package for statistical software `R` for ecologists and managers (Genu et al. 2021). The package allows to carry MSE with the two control rules: Potential Biological Removal (PBR) and the Removals Limit Algorithm (RLA). We added a new one: Anthropogenic Removals Threshold or, simply, ART.

Material and Methods

Notation

Notations are summarized in Table 1. Let $\log\mathcal{N}(\text{location}, \text{scale})$ denotes the log-normal distribution of parameters location and scale. The $\widehat{\ }$ notation flags a point estimate of a parameter (*e.g.* a quantile from a posterior distribution).

Name	Type	Meaning
K	Integer	Carrying capacity (same unit as N_t, N_t^{obs} or R_t)
N_t	Integer	True abundance (in number of individuals) at time t
N_t^{obs}	Integer	Observed abundance (in number of individuals) at time t
cv_t	Positive real	Coefficient of variation associated with N_t^{obs}
R_t	Integer	Removals (in number of individuals) at time t
D_t	Positive real	Depletion at time t: ratio of N_t over K
ρ	Positive real	Removal rate
r^*	Positive real	Population growth rate at the MNPL
r	Positive real	Current population growth rate
MNP	Positive real	Maximum Net Productivity: the maximum possible *per capita* rate of increase per year
MNPL	Proportion	Maximum Net Productivity Level
z	Positive real	Shape parameter of the Generalized Logistic Population Growth model
$r_{\max}$	Positive real	Maximum theoretical or estimated productivity rate; related to MNP
F_{R}	Proportion	Recovery factor
$\text{N}_{\min}$	Integer	Minimum population estimate (Wade 1998)
IPL	Proportion	Internal Protection Level; a fraction of K
w_t	Positive real	weight for the likelihood (Eq. 14)
cv_σ	Positive real	Coefficient of variation associated with environmental stochasticity
ε_t, σ	Positive real	Environmental stochasticity

Table 1: **Notations**.

Potential Biological Removal

The calculation of PBR is model-free:

$$\text{PBR} = N_{\text{min}} \frac{1}{2} r_{\text{max}} F_{\text{R}},$$

N_{min} is an estimate of minimum population size, $\frac{1}{2} r_{\text{max}}$ one half of the maximum theoretical net productivity rate, and F_{R} a recovery factor between 0.1 and 1 (Wade 1998). The computation of PBR does not require data on removals.

Removals Limit Algorithm

The other harvest control rule currently in use is the Removals Limit Algorithm (RLA). Its computation requires both a time-series of abundance/biomass estimates (whereas PBR only requires one such estimate) and a time-series of removals (whereas PBR requires none). RLA is a variant of the Catch Limit Algorithm for baleen whales (Cooke 1999):

$$N_{t+1} = N_t + rN_t \left(1 - \left(\frac{N_t}{N_0}\right)^2\right) - R_t, \tag{1}$$

where N_t and R_t are respectively the abundance/biomass and removals at time t. The computation of the RLA control rule for setting a removals limit (as a fraction of the best available abundance estimate) is:

$$\text{removals limit} = r \times \max\left(0, D_T - \text{IPL}\right), \tag{2}$$

where T is the current year, D_T current depletion (that is, $D_T = \frac{N_T}{K}$, K being the carrying capacity) and IPL (Internal Protection Level) the depletion level below which the limit is set to 0. Both r and D_T are estimated from the model defined by Eq. 1 in a Bayesian framework and removals limit is computed from the joint posterior distribution of $(r,\ D_T)$. A point estimate is used in practice by selecting a quantile of the posterior distribution to account for uncertainty.

Candidate Control Rules

The PBR control rule takes a value for r_{max} as an input while the RLA control rule uses a posterior distribution of r (from the model defined by Eq. 1). For most species, both r_{max} or r are unknown: a default value can be used for PBR, or r needs to be estimated from a prior and data. This knowledge gap may be exploited to argue against the use of either of these rules using uncertainty distortion strategies (Schweder 2000; Rayner 2012). Devising a new rule to set a removals limit that does not directly hinge on knowledge of this input is desirable to (i) avoid any strategic mis-representation of uncertainty (see Rayner 2012); and (ii) diversify options for discussions during the policy process. We developed candidate control rules based on the same data requirements as the RLA, namely a time-series of removals and at least one estimate of abundance that are fed into a statistical model. The statistical model is, however, different in **how** it incorporates the removals data. In Eq. 1, removals are treated as a known covariate. Below, we develop a stochastic model for removals directly.

Development of a stochastic Surplus Production Model
Operating models for PETS are often based on Surplus Production Models (SPM) which are standard models of population dynamics in situations of strong uncertainty and low information. SPMs seek to encompass important population processes governing the dynamics of abundance change over time:

next abundance = previous abundance+recruitment+growth−natural mortality−anthropogenic removals

Density-dependence is taken into account (Pella & Tomlison, 1969), assuming a first-order Markovian process on abundance:

$$N_{t+1} = N_t + r^* \left(\frac{z+1}{z}\right) N_t \left(1 - \left(\frac{N_t}{K}\right)^z\right) - R_t \tag{3}$$

Setting $z = 1$ gives the Schaefer model: N_t and R_t are respectively the abundance/biomass and removals at time t, K the carrying capacity and r^* the growth rate at the Maximum Net Productivity Level (MNPL; r^* is also known as the Maximum Sustainable Yield Rate). Incorporating environmental variability (the so-called process noise ε_t) in a multiplicative way in Eq.3 yields:

$$N_{t+1} = \left\{N_t + r^* \left(\frac{z+1}{z}\right) N_t \left(1 - \left(\frac{N_t}{K}\right)^z\right) - R_t\right\} \varepsilon_t. \tag{4}$$

where ε_t is assumed to be unbiased ($\mathbb{E}[\varepsilon_t] = 1$) and homoskedastic ($\mathbb{V}[\varepsilon_t] = \sigma^2$).Assuming a simple relationship between removals R_t and abundance N_t:

$$R_t \quad = \quad \rho N_t \tag{5}$$

where $\rho \in]0, 1[$ is a time-invariant removal rate (Bousquet et al. 2008; Bordet & Rivest 2014), the removal process becomes:

$$R_{t+1} = \left\{R_t + \frac{z+1}{z} r^* R_t \left(1 - \left(\frac{R_t}{K\rho}\right)^z\right) - \rho R_t)\right\} \varepsilon_t \tag{6}$$

The set of parameters in Eq. 6 is $\theta = \{K, \sigma, \rho, r^*\}$. Parameter z is usually fixed rather than estimated. Setting $z = 2.39$ corresponds to a MNPL of 60% of K as customarily assumed for marine mammals. Eq. 5 is a simplifying assumption that allows to link the abundance and removal processes. Stochasticity is introduced in Eq. 6 for estimating a removal rate from data, meaning that removals are used as an index of abundance.

Reparametrization
Following Bordet & Rivest (2014), let

$$Z_t = \frac{N_t}{K} \left(\frac{r^*(z+1)}{z - \rho z + r^*(z+1)}\right)^{\frac{1}{z}}$$

which is well defined for $z - \rho z + r^*(1+z) > 0$, that is

$$\rho \quad < 1 + r^* \tfrac{z+1}{z}.$$

With $z > 0$ this assumption is not restrictive since $0 < \rho < 1$. Eq. 4 and 6 can be re-arranged:

$$\begin{aligned} Z_{t+1} &= \left(1 - \rho + r^* \frac{z+1}{z}\right) Z_t \left(1 - Z_t^z\right) \varepsilon_t, \\ R_{t+1} &= \left(1 - \rho + r^* \frac{z+1}{z}\right) R_t \left(1 - \{D(\theta) R_t\}^z\right) \varepsilon_t \end{aligned}$$

with $Z_t = D(\theta) R_t$ and

$$D(\theta) \quad = \quad \frac{1}{K\rho} \left(\frac{r^*(z+1)}{z - \rho z + r^*(z+1)} \right)^{\frac{1}{z}}.$$

Positive removals imply $R_t \leq \frac{1}{D(\theta)}$. To simplify notations and to adopt a more conventional Markovian writing:

$$R_t \quad = \quad g(R_{t-1}, \theta) \varepsilon_t \tag{7}$$

where g, which is neither linear nor log-linear, is:

$$g(R_{t-1}, \theta) = \left(1 - \rho + r^* \frac{z+1}{z}\right) R_{t-1} \left(1 - \{D(\theta) R_{t-1}\}^z\right). \tag{8}$$

A sequence of observed removals $(R_0, \ldots, R_T)$ informs on θ via a likelihood function:

$$\ell(R_0, \ldots, R_T | \theta) \quad = \quad \ell(\{R_t\} | \theta) = \prod_{t=1}^{T} f(R_t | R_{t-1}, \theta) \tag{9}$$

where each conditional density function $f(R_t | R_{t-1}, \theta)$ is determined by a choice on the distribution of ε_t. Although the considered quantities are discrete and bounded in our setting, a log-normal assumption is a customary choice to model environmental stochasticity:

$$\varepsilon_t \quad \sim \quad \log \mathcal{N}\left(-\frac{\sigma^2}{2}, \sigma\right),$$

which implies both $\mathbb{E}\left[\varepsilon_t | \mathcal{F}_{t-1}\right] = 1$ and $\mathbb{V}\left[\varepsilon_t | \mathcal{F}_{t-1}\right] = \sigma^2$. Accordingly, given Eq. 7, the conditional density of R_t in Eq. 9 becomes, for $t > 1$:

$$f(R_t | R_{t-1}, \theta) = \frac{1}{\sqrt{2\pi}\sigma R_t} \exp\left(-\frac{1}{\sigma^2} \exp\left\{ \log R_t - \log g(R_{t-1}, \theta) + \frac{\sigma^2}{2} \right\}^2 \right). \tag{10}$$

where $g(R_{t-1}, \theta)$ is given by Eq. 8.
One of the parameters in θ, K needs data on absolute abundance. Denote $\mathcal{I}$ the years for which an abundance estimate N_t^{obs}, observed with noise, is available. We denote $\mathcal{J}$ the years for which removals are observed, with $\mathcal{I} \subset \mathcal{J}$. The true abundance in year $t \in \mathcal{I}$ is

$$N_t = \frac{R_t}{\rho}.$$

Assuming a log-normal distribution for observation errors ϵ'_t, $\forall t \in \mathcal{I}$:

$$N_t^{\text{obs}} | R_t, \theta, \tau_t = N_t \exp(\epsilon'_t) \text{ with } \epsilon'_t \sim \log\mathcal{N}\left(-\frac{\tau_t^2}{2}, \tau_t\right),$$

where $\tau_t = \sqrt{\log\left(1 + \text{cv}_t^2\right)}$ and cv_t is the coefficient of variation associated with the estimated abundance N_t^{obs}. The observation model for each observed abundance datum is:

$$N_t^{\text{obs}} | R_t, \theta, \tau_t \sim \log\mathcal{N}\left(\log R_t - \log\rho - \frac{\tau_t^2}{2}, \tau_t\right) \quad (11)$$

The joint likelihood of the observed abundances and removals data is

$$\ell_\theta\left(\left\{N_t^{\text{obs}}\right\}_{t\in\mathcal{I}}, \{R_t\}_{t\in\mathcal{J}}\right) = \ell\left(\left\{N_t^{\text{obs}}\right\}_{t\in\mathcal{I}} | \{R_t\}_{t\in\mathcal{J}}, \theta\right) \times \prod_{t\in\mathcal{J}} \ell\left(\{R_t\}, \theta\right) \quad (12)$$

where $\ell\left(\{R_t\}, \theta\right)$ is given by Eq. 9. Under the assumption that abundances are observed independently from removals and given Eq. (11), one has:

$$\ell\left(\left\{N_t^{\text{obs}}\right\}_{t\in\mathcal{I}} | \{R_t\}_{t\in\mathcal{J}}, \theta\right) = \prod_{t\in\mathcal{I}} \frac{1}{\sqrt{2\pi}N_t^{\text{obs}}\tau_t} \exp\left(-\left(\log\left(\frac{\rho N_t^{\text{obs}}}{R_t}\right) + \frac{\tau_t^2}{2}\right)^2 \frac{1}{2\tau_t^2}\right). \quad (13)$$

We wrote the joint likelihood (Eq. 12, Ouzoulias et al. 2024) in programming language `Stan` (Carpenter et al. 2017).

Initial conditions
For practical reasons, the initial depletion D_0 at the start of the time-series of removals, instead of K, is estimated: $D_0 = \frac{N_0}{K}$. Initial abundance N_0 is typically unknown for PETS and the first abundance estimate available may not even match the start of the observed removals time-series. In that case, information on initial depletion D_0 may be elicited from expert knowledge or historical data, and given a prior distribution: it may be easier to elicit a prior on depletion (a quantity expected to be bounded between 0 and 1) than on K directly. In practice, K is deduced from D_0 and the first observed abundance estimate that is available. The set of parameters to estimate is now: $\theta = \{r^*, \sigma, \rho, D_0\}$.

Anthropogenic Removals Threshold (ART)
The stochastic SPM assumes a crude proportionality between removals and abundance, and stationarity in ρ, the removal rate, which is at odds with the very purpose of managing

removals. If management is meant to be effective, it will take action to precisely change the level of removals. By definition, management aims at changing ρ over time so the model is clearly wrong once management is implemented. Before management is implemented, stationarity is an assumption as there is typically little knowledge or data are too noisy to test it. To obviate this issue while retaining a parsimonious model with 4 parameters, we used a *weighted* likelihood approach to progressively down-weigh data extending the furthest back in time (*i.e.*, to consider that the policy relevance of statistical information provided by each datum in a sample depends on how far back in time the datum was collected). The likelihood $\ell(\{R_t\}|\theta)$ is replaced by

$$\ell^{\boldsymbol{w}(\eta)}(\{R_t\}|\theta) \quad = \quad \prod_{t=1}^{T} \left(f\left(R_t|R_{t-1},\theta\right)\right)^{w_t(\eta)} \tag{14}$$

where the weights $w_t(\eta)$ provide a kernel-based representation of the score function

$$s(\theta) \quad = \nabla_\theta \; \ell(\{R_t\}|\theta).$$

The weights $w_t(\eta)$ should be a bounded differentiable non-negative function of t that may depend on a parameter η which can be consistently estimated by $\hat{\eta}$, such that

$$\sup_{R_t} |w(t,\hat{\eta}) - c| \quad \xrightarrow[p]{t\to\infty} \quad 0 \quad \text{almost surely}$$

where c is a positive constant. The following choice (Gaussian kernel):

$$w_t(\eta) \quad = \quad \exp\left(-\frac{(T-t)^2}{2\eta^2}\right)$$

obeys these requirements (with $c = 1$). η was fixed instead of estimated so that data older than 50 years contribute less than 0.05 to the likelihood during estimation ($w_t = 0.05$ for $(t - 50)$). This choice ($\eta = 20.4$) is arbitrary but was found to work well in practice. Capitalizing from the stochastic SPM (Eq. 14), we propose two candidate control rules (as a fraction of the best available abundance estimate) which we call *Anthropogenic Removals Threshold* (ART) to emphasize that the quantity derived from these control rules represents a threshold beyond which conservation objectives run a high risk of not being met. The first candidate is simply the posterior mean of the quantity:

$$\text{candidate}_1 = \rho \times F_{\text{R}} \tag{15}$$

where F_{R} is a recovery factor chosen between 0.1 and 1 (as in the PBR control rule). This rule adapts the historical removal rate and does not directly rely on an estimate of carrying capacity or population growth rate as the RLA control rule (although both a carrying capacity and a population growth rate are in θ). The second candidate takes stock of any decline in abundance to negatively feedback on the removals limit:

$$\text{candidate}_2 = \rho \times F_{\text{R}} \times \min\left(1, \exp\left(\beta\right)\right) \tag{16}$$

where β is the slope of a regression line through the abundance estimates (scaled by the first estimate and then log-transformed) and estimated using a weakly-informative prior (namely the 'skeptical' prior of Cook et al. (2011)) that favours the hypothesis of no trend over time. This candidate rule operationalizes the principle on non-deterioration whereby populations or species in need of restoration (that is, that are depleted) should not be allowed to deteriorate further. If no trend or a positive trend in abundance is evidenced, candidate_2 is equivalent to candidate_1. Both candidate_1 and candidate_2 can be computed for the same data necessary to compute RLA, and their posterior mean approximated by the average over a sample from the posterior distribution of θ.

('Harvest') Control rules

We tested 4 control rules for managing anthropogenic removals of PETS:

- the PBR rule of Wade (1998) with N_{min} defined as the 20% quantile of a log-normally distributed abundance estimate N_T^{obs}: $\text{PBR} = N_{\text{min}} \frac{1}{2} r_{\text{max}} F_{\text{R}}$;
- the RLA rule, with $\text{RLA} = N_T^{\text{obs}} \times \text{removals limit} = N_T^{\text{obs}} \times r \times \max(0, D_T - \text{IPL})$;
- the candidate_1 ART, with $\text{ART}_1 = N_T^{\text{obs}} \times \text{candidate}_1 = N_T^{\text{obs}} \times \rho \times F_{\text{R}}$; and
- the candidate_2 ART, with $\text{ART}_2 = N_T^{\text{obs}} \times \text{candidate}_2 = N_T^{\text{obs}} \times \rho \times F_{\text{R}} \times \min(1, \exp(\beta))$.

All rules need tuning. For PBR, ART_1 and ART_2, this process means the testing of different values of F_{R} to identify the minimum one that allows to reach the conservation objective. For RLA, tuning is achieved by testing different quantiles of the posterior distribution of Eq. 2. That quantile tuning was not carried out with ART_1 or ART_2 stemmed from the typically tight posterior concentration observed when estimating ρ during the development of the stochastic SPM. In contrast, posterior concentration does not occur because the log-normal likelihood assumed for Eq. 1 when estimating removals limit is down-weighted by a fixed factor $\frac{1}{16}$ to limit the speed at which the management procedure responds to feedback (Cooke 1999).

Simulations

The operating model used in population dynamics simulations was a stochastic and age-disaggregated version of a generalized logistic model of population dynamics (Genu et al. 2021). Given initial conditions, biological parameters and removals, abundance data are generated at each time step. Life-history parameters of the the Harbour Porpoise (*Phocoena phocoena*) in the North Sea were inputed to the operating model. A hundred (100) simulations were carried out: for each a hypothetical population of harbour porpoises was depleted with unmanaged anthropogenic removals for 50 years before implementing management procedures and specific control rules. A time-series of removals as long as 50 years is unusual in general, but one is available for harbour porpoise in the North Sea. A distribution of initial depletion levels was induced between 30% and 60%. Important biological inputs include the Maximum Net Productivity (MNP) and MNPL, which are usually unknown in most cases. To reflect that uncertainty, a range of plausible values for small cetaceans were considered.

Scenarios

We evaluated control rules on three scenarios: a base case scenario whereby unbiased but noisy data are assumed to be available and collected; and two so-called robustness trials. In the first trial, estimates of abundance have a systematic bias resulting in an overestimation by a factor 2. In the second, removals' estimates were assumed to be biased downward, resulting in an underestimation of true removals by a factor 2. The two robustness trials were found to be the most challenging ones in a previous investigation (Genu et al. 2021). The MSE is summarized on Figure 1. The conservation objective for "long-term viability" was defined as to restore or maintain population size to at least 60% of carrying capacity (K) over a time horizon of 50 years with the probability of 0.9.

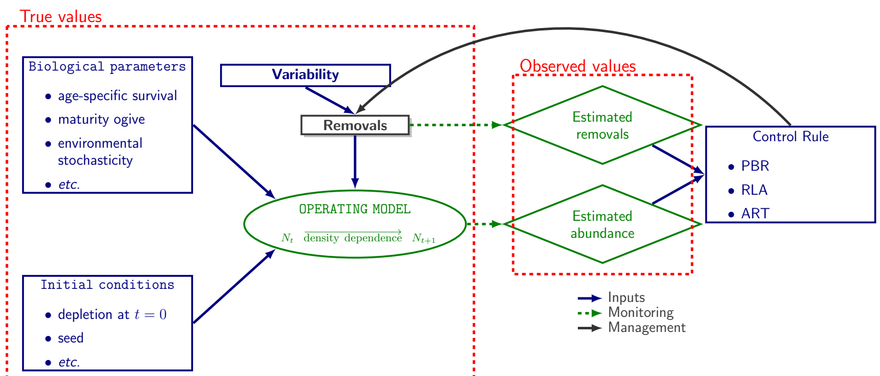

Figure 1: **Simulation workflow.** Schematic representation of the workflow for simulations. Population dynamics (N denotes abundance) are simulated from biological parameters (life-history data, true removal rate etc.). Monitoring allows to collect data but these data are noisy: they always include observation noise and, depending on robustness trials, can be biased. Data are used as inputs in control rules for managing removals.

Results

A Shiny application for visualizing results is available at `https://pelabox.univ-lr.fr/pelagis/DART/`. Results will be detailed and discussed during the talk. The main one is shown on Figure 2.

Conclusion

Future research directions will close the talk. This research has been published in *PeerJ* (Ouzoulias et al. 2024).

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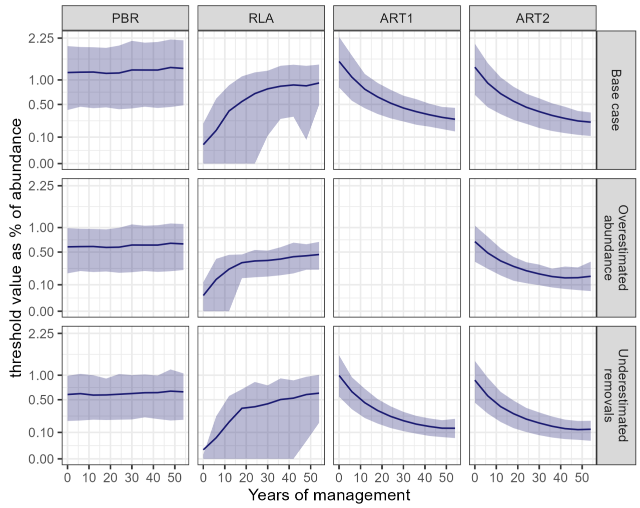

Figure 2: **Different paths to managing removals to ensure long-term population viability** The behaviour of the removals limit set by the different control rules was very different, with only ART achieving long-term viability and to minimize removals limits over time. Average and 80% confidence bands (from the 100 simulations) are depicted.

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