Agenda Item 2

Review of New Information on Threats to Small Cetaceans (reporting cycle 2017 only)

Bycatch

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Development of a Removals Limit Algorithm (RLA) to set to Anthropogenic Mortality of Small Cetaceans to meet Specified Conservation Objectives; with an Example Implementation for Bycatch of Harbour Porpoise in the North Sea

Action Requested

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Development of a Removals Limit Algorithm (RLA) to set limits to anthropogenic mortality of small cetaceans to meet specified conservation objectives, with an example implementation for bycatch of harbour porpoise in the North Sea

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EXECUTIVE SUMMARY

A Removals Limit Algorithm (RLA) is developed to set limits to anthropogenic mortality of small cetacean populations that allow specified conservation objectives to be met. The RLA is similar in concept to the Catch Limit Algorithm (CLA) of the IWC's Revised Management Procedure. The RLA comprises a simple one-line population model which is fitted to a time series of estimates of abundance to estimate population growth rate and depletion, which are then used in a removals calculation. The RLA is tuned through computer simulation to set limits to anthropogenic mortality that allow the specified conservation objectives to be met. The robustness of the RLA is determined by assessing its performance in a range of computer simulation tests describing uncertainty in our knowledge of population dynamics, the data and the wider environment. The RLA developed here is illustrated in an example implementation for harbour porpoise in the North Sea using estimates of abundance from the three SCANS surveys with initial depletion determined using a time series of historical bycatch estimates constructed by making a number of strong assumptions about effort for most fleets and appropriate bycatch rates. The RLA developed here is entirely dependent on the conservation objectives assumed; the work would need to be repeated if the conservation objectives were different.

1. INTRODUCTION

Fisheries bycatch has been identified as the greatest source of mortality for small cetaceans worldwide (Read et al. 2006); in European Atlantic waters the harbour porpoise and common dolphin are particularly susceptible (e.g. ICES 2016, 2017; Vinther & Larsen 2004; Tregenza et al. 1997a, b). Mechanisms for how limits can be set for marine mammal bycatch and other anthropogenic mortality have been discussed for many years. In the USA, the Potential Biological Removal (PBR) equation (Wade 1998) is used to assess when anthropogenic mortality is too high and management action is required. The procedure for implementing PBR within the US government Marine Mammal Protection Act is described in full in MMPA (2018). The International Whaling Commission has developed a Revised Management Procedure (RMP) for setting limits to catches of baleen whales (IWC 2012).

In Europe, these issues were considered at a joint ASCOBANS/IWC workshop (IWC 2000). At that workshop, a very simple population dynamics model of a nominal harbour porpoise population, with a maximum rate of increase of 4% per annum, was used to determine that a mortality rate of 1.7% of population size would allow a population to reach and be maintained at 80% of carrying capacity over a very long time period.

This figure of 1.7% has since been adopted by ASCOBANS, OSPAR and the European Commission (see ICES 2012) but it is a very blunt instrument for setting limits to anthropogenic mortality. At an ASCOBANS workshop (ASCOBANS, 2015), it was generally agreed that limits for bycatch were useful but the appropriateness of the 1.7% limit should be reviewed.

With this in mind, the primary aim of this work was to develop a "management procedure" for setting robust limits to anthropogenic mortality of small cetaceans, the main source of which is fisheries bycatch. This work revisits previous work conducted as part of the SCANS-II and CODA projects that had a focus on bycatch of harbour porpoise and common dolphin, respectively (SCANS-II 2008; CODA 2009; Winship et al. 2006, 2009; Winship 2009). The development of the procedure has been reconsidered from scratch but uses the previous work as a reference and there are thus strong parallels to previous work.

The procedure developed here to set limits to anthropogenic mortality of small cetacean populations is named the Removals Limit Algorithm (RLA). It is similar in concept to the Catch Limit Algorithm (CLA) that lies at the centre of the IWC's Revised Management Procedure (RMP, IWC 2012). The major difference is that the overall purpose of the RMP is to manage commercial whaling and its objectives are thus not only to ensure a low risk of population depletion as a top priority but secondarily to maximise catches and minimise variation in catch limits. These secondary objectives are not relevant to the RLA (see section 2.3), although fishery-related objectives could in principle be included. Another difference is that while the primary source of removals data used by the CLA are the assumed known catches of baleen whales, the RLA uses estimates of bycatch or other incidental anthropogenic mortality, which are both uncertain and potentially biased.

Note that both the CLA and the RLA set limits to all anthropogenic mortality, whatever the cause.

The basic idea is to use survey estimates of abundance to estimate the level of depletion of a population (expressed as a proportion of its carrying capacity, i.e. unimpacted abundance), and to use a simple algorithm to set limits to removals that will ensure that the population ultimately meets conservation objectives specified in terms of its depletion. These objectives must be quantitatively defined so that the ability of the procedure under development to meet them can be assessed.

The robustness of the RLA is determined by testing it through computer simulation using a realistic population model that is deemed to serve as "truth". The simulations test how the population responds, under management of anthropogenic mortality using the RLA, against a range of plausible uncertainties in knowledge of population dynamics, the wider environment and the data used.

A secondary aspect of this work was to implement the developed procedure in a real example: harbour porpoise in the North Sea subject to fisheries bycatch. The availability of new abundance estimates from the SCANS-III surveys (Hammond et al. 2017) and somewhat improved series of estimates of bycatch mortality for this species in this region mean that this example implementation is informative. However, the bycatch limits calculated are entirely dependent on the conservation objectives chosen (see section 2.3), the simulation tests (see section 2.5) and how the results of the simulation tests are interpreted (see sections 3.4 and 4).

It is important to state that the RLA calculates <u>limits</u> to anthropogenic mortality, not targets, somewhat analogous to speed restrictions for traffic on roads. The restriction is an upper limit; actual mortality/speed can be lower depending on circumstances. The purpose here is to provide managers with information on levels of mortality that should not be exceeded if specified conservation objectives are to be met. How these upper limits are used for management purposes is a policy matter.

In this report, we first describe the framework for developing the RLA in general terms (section 2) and then go on to describe the development of the population model used for simulation, the form of the RLA itself, the simulation testing framework, the range of simulation tests performed, and the performance metrics used to determine the robustness of the RLA under simulation (section 3). Section 4 describes the results of the simulation testing to determine robustness. In section 5, we present an example implementation of the RLA using data for the abundance and bycatch of harbour porpoise in the North Sea. A brief discussion of the work is given in section 6.

2. FRAMEWORK FOR RLA DEVELOPMENT

2.1 Population model

The first task is to construct a model of the dynamics of a small cetacean population to be treated as "truth" during simulation testing. The model should be based on realistic values of population parameters from first principles, the literature and elsewhere (see section 3.1). The intention is that it mimics the dynamics of a real population sufficiently well to serve as an appropriate framework to test the performance of the Removals Limit Algorithm (RLA, see section 3.2)) against a range of uncertainties in our knowledge (see section 3.4). The model does not need to be the best possible description of any particular population.

During simulations, the population model is used to generate survey estimates of population size, with a given level of uncertainty (CV), that are used in the fitting of the RLA. The fitted RLA is then used to calculate the limit to the number of animals that could be removed as a result of human activities (from any source) in subsequent years. Estimates of the number of animals actually removed are subtracted from the population each year.

Here we use the harbour porpoise in the North Sea as a basis for the population model but, because the model is largely generic, it is readily modified to mimic the dynamics of any small cetacean species, for example the common dolphin, or species of pinniped, which may be under pressure from fisheries bycatch or other forms of human activity, such as shooting seals around fishing nets.

2.2 Removals Limit Algorithm

The procedure that sets limits to anthropogenic mortality that will allow the conservation objectives (see section 2.3) to be met is here called the Removals Limit Algorithm (RLA); this procedure is equivalent to the Catch Limit Algorithm (CLA) of the IWC's RMP. The RLA is fitted to a time series of estimates of abundance from surveys and the resulting estimate of depletion (the population expressed as a proportion of its carrying capacity, i.e. unimpacted abundance) is used to set a nominal removals limit through a simple calculation (see section 3.2).

2.3 Conservation objectives

An RLA can only be developed if there are quantitatively defined conservation objectives against which its performance can be tested. Previous work on the development of procedures to set limits to anthropogenic mortality of small cetaceans (SCANS-II 2008; CODA 2009; Winship et al. 2006, 2009; Winship 2009) used the ASCOBANS interim conservation objective as a basis - to allow populations to recover to and/or maintain 80% of carrying capacity in the long term. Converting this into a quantitative objective that can be used to assess the performance of an RLA requires some interpretation about the probability that a population achieves 80% of carrying capacity and the meaning of "long term". This has previously been discussed at the ICES Working Group on Marine Mammal Ecology (ICES 2013).

In the absence of alternative policy guidance, and with the agreement of JNCC, the quantitative conservation objective used here was that a population should recover to or be maintained at 80% of carrying capacity, on average, within a 100-year period. In simulation tests (see below), this equates to the median population level being at 80% of carrying capacity. Discussion of other conservation objectives is included in section 6.

2.4 Simulation testing framework

An RLA must be robust to uncertainties in our knowledge yet still allow conservation objectives to be met; the only practical way to test and determine this is through computer simulation. Therefore, a simulation testing framework is needed to determine whether or not a candidate RLA is able to set removal limits that allow conservation objectives to be met under scenarios encompassing a plausible range of uncertainty (see section 3.3).

2.5 Simulation tests

In the context of development of a procedure to set limits to anthropogenic mortality of small cetaceans, uncertainty is equivalent to failures of the assumptions made in the population model about the dynamics of real populations (see section 3.1), about the properties of the abundance or bycatch data provided to the RLA (see section 3.2) or about the wider environment supporting the populations. Sources and plausible levels of uncertainty to which the RLA should be subjected need to be specified and implemented in a series of simulation tests (see section 3.4). How well the RLA meets the conservation objectives after a simulation test should be determined by a set of performance metrics (see section 3.5).

Before testing robustness to uncertainty, initial simulations need to be done to "tune" the RLA so that the limits to anthropogenic mortality calculated allow the population to meet the specified conservation objectives. This can be achieved by defining a "base case" simulation that represents a realistic appraisal of the true situation and running it with a range of values of a tuning parameter, γ. The largest value of γ that allows conservation objectives to be met is then used in subsequent robustness simulations. Note that γ will be different for different assumed levels of maximum net productivity (see section 3.4).

2.6 Assessment of Removal Limit Algorithm

The end point of the simulation testing is to determine the robustness to plausible uncertainties of the RLA, as defined, to meet the specified conservation objectives. A decision can then be taken on whether or not the tested RLA is robust or whether additional development and/or simulation testing is required to modify or tune the RLA further.

3. DEVELOPMENT OF THE RLA

3.1 Population model

The population model is based on the harbour porpoise in the North Sea. It is age-structured, with a maximum life span of 22 years. A Pella-Tomlinson like density dependence is used to adjust birth rates

$$birth\ rate\ = b_K + (b_{max} - b_K)\left\{1 - \left(\frac{N}{K}\right)^z\right\}$$

where b_K is birth rate at carrying capacity K, b_{max} is maximum birth rate, N is population size, and the exponent z sets the population level at which maximum productivity occurs. N/K is the depletion level of the population, also referred to as D.

Birth rate, b_r, is calculated every year and the number of new born individuals is then calculated as:

$$newborns = \sum b_r N_a M_a$$

where N_a is the number of animals at age a, and M_a is the estimated proportion of the population that is mature at age a. Sex ratio is assumed to be 1 to 1.

Data on age at sexual maturity from harbour porpoises that stranded along the North Sea coasts of the UK and Denmark were taken from Winship (2009). The proportion mature at age, M_a, was estimated from these data using logistic regression and kept fixed for all simulations.

Natural and anthropogenic mortality are included using instantaneous survival rates. Base natural survival rates were fixed for each age as 0.85 for age 0, 0.87 for age 1 and 0.91 for age 2+ (Winship 2009) but see also below. Anthropogenic mortality rates vary from year to year depending on population size and the total number of removals observed/predicted for that year. Vulnerability to removals was set to be 50% higher for age 0 and age 1 than for all other ages based on results from population models fitted to data on harbour porpoise in the North Sea (Winship et al. 2007).

Within a time-step (year), the population dynamics processes were applied as follows:

1. **Births**: the number of new born animals was calculated using the population size at the beginning of the year;
2. **Mortality**: natural and anthropogenic mortality was applied to all age classes.
3. **Aging**: the age of the population was increased by one year and the new born animals (calculated in step 1) were aggregated into an age 0 age class.
4. **Survey**: simulated survey estimates were drawn (every 6 years in the base case), following the approach described in IWC (2004).

During simulation testing of the RLA (see section 4) the population model was tuned to realise different maximum net productivity (MNP) rates by modifying the density dependent and survival parameters of the model.

3.2 Removals Limit Algorithm

The RLA is a simple population dynamics model describing a population with density dependent growth and subject to anthropogenic removals. The RLA is fitted to time series of data on abundance (population size) and accounts for the number of removals, each with associated uncertainty. Survey estimates are assumed independent among years.

The dynamics of the RLA are determined by a population growth parameter, μ, that, dependent on the depletion of the population, D, determines the number of new individuals added to the population

$$N_{t+1} = N_t - c_t + 1.4184\, \mu\, N_t\{1 - {D_t}^2\}$$

where N_t is the population size at the beginning of year t, c_t is the number of animals removed during year t, μ is the growth parameter and D_t is population depletion at time t, that is N_t/K, where K is carrying capacity.

Bayesian methods were used to fit the model, which required prior distributions to be assigned to the unknown parameters to be estimated. The parameter μ was assigned a uniform distribution between 0 and 0.05, which, when multiplied by the constant 1.4184, allows population growth up to 7% per annum. This encompasses the value of 4% found in an analysis of harbour porpoise growth rates in the Bay of Fundy and the Gulf of Maine (Woodley & Read 2011) but is restricted compared to the uncertainty analysis conducted by Caswell et al. (1998), which found rates of around 10% were more plausible. The other estimable parameter of the RLA, depletion, was assigned a uniform prior distribution between 0 and 1.

The IWC's CLA also includes a bias parameter that is multiplied by the survey abundance estimate, N_t. The purpose of the bias parameter in the CLA is to reduce the variance of the remaining parameters because otherwise removal limits can change markedly each time a new survey estimate is added and the algorithm is re-fitted (Cooke 1999). In our simulation trials, inclusion of a bias parameter led to poor fitting of the RLA and it was thus omitted.

Another feature of the IWC's CLA is the down-weighting of the log likelihood during model fitting, a departure from the Bayesian paradigm. This down-weighting was found to improve the fit of the CLA to the data and improve performance. In the RLA, we also use the down-weighting of w = 1/16 used in the CLA. Other down-weightings of the log likelihood were not explored.

3.2.1 RLA model fitting

The RLA was fitted to the input data on abundance using Markov chain Monte Carlo (MCMC) methods. This involved using five different functions to (a) find the likelihood of the proposed parameters in the prior distributions, (b) find the likelihood of the observed simulated abundance data given the parameters (c) bind these two likelihoods to give the posterior distribution, (d) generate a new set of parameters and (e) implement the Metropolis Hastings algorithm. The R code to implement the RLA, which shows these functions, is given in Appendix 2.

3.2.2 Setting limits to removals

Based on the posterior distribution of the fitted parameters, the RLA sets limits to removals with reference to an Internal Protection Level (IPL) using the following removals calculation:

- If estimated depletion is less than the IPL, removal limit = 0;
- Otherwise, removal limit = $\gamma * \mu * N_t * (D_t$ - IPL)

where γ is a tuning parameter set to ensure that the conservation objectives are met, and IPL is set to a depletion of 0.54, the same level as used in the IWC's CLA.

The removal limit is taken to be the median of the posterior distribution of the nominal limit based on the fitted values of μ and D_t.

If the IPL parameter were changed, this would result in a different value of the tuning parameter γ to ensure that the conservation objectives were met. An alternative way to implement tuning would be to use a different value of the posterior distribution. For example, in the CLA, the equivalent catch control law replaces γ with a constant and uses the 40.2th percentile of the posterior distribution of the nominal limit. The use of the 40.2th percentile also means that tighter posterior distributions resulting from more precise abundance estimates will give larger removals limits, and *vice versa*. This aspect of the CLA was not included in the RLA.

3.3 Simulation testing framework

To initiate each simulation, the initial age structure of the population must be determined. The initial number of animals in each age group, needed to initiate the simulation, was set according to the exponential distribution that most resembled the observed frequency of bycaught animals in Danish and UK fisheries (see Figure 1). The age structure of the population changes through the simulation, depending on the birth and survival rate parameters of the population model (see section 3.1).

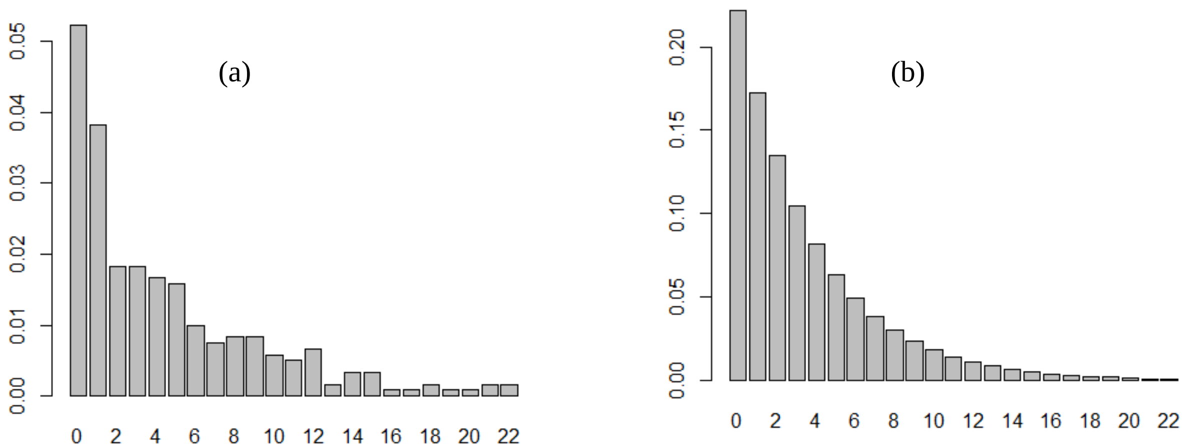


Figure 1. (a) Observed bycatch age distribution (from data used by Winship 2009); **(b)** derived initial population structure presented as a proportion of the population at each annual age class.

In order to start every simulation at carrying capacity and with a stable population structure, for each set of population parameters the population was simulated over a 400-year training period.

Then, each simulation proceeded according to the following steps:

1. The population model was run for 30 years using historical removal (bycatch) data, with age-specific vulnerabilities as stated above, to deplete the population to a specified level. The actual number of animals removed each year was drawn randomly from the data (zero-truncated normal distribution) with a specified CV.

2. The RLA was fitted to the survey abundance estimates drawn from the population model (at the specified interval), starting immediately after the third of the three existing estimates of abundance from SCANS surveys (Hammond et al. 2017). Survey abundance estimates were generated according to the procedure used for implementing the CLA described in IWC (2004).
3. The fitted values of μ and D_t were used in the removals calculation to set the annual removal limit for the period until the next survey was due, using a specified value of γ.
4. The number of animals removed each year was drawn randomly from the removal limit (zero-truncated normal distribution) with a specified CV.
5. The population model was run for additional years until the next survey abundance estimate was due.
6. Steps 2-5 were repeated until the 100-year simulation period was complete.

Each simulation was repeated 100 times. Figure 2 illustrates an example population trajectory subject to these simulation steps.

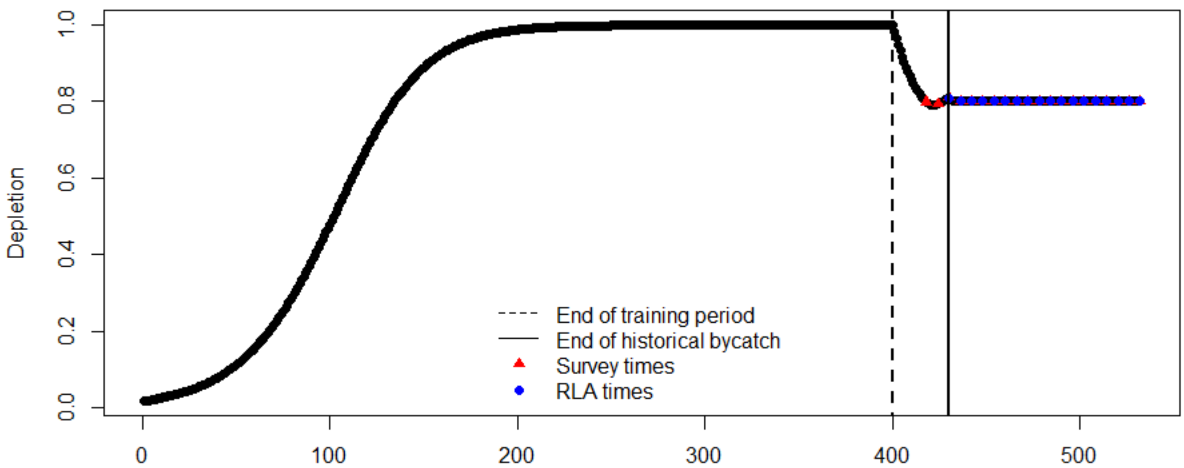


Figure 2. Illustration of the population trajectory on the scale of depletion (N_t /K) subject to a simulation over 530 years. The initial training period to achieve carry capacity and a stable age structure is 400 years. Depletion as a result of historical bycatch, to 0.8 in this case, occurs over years 400-430. The RLA is first fitted when there are three survey estimates of abundance available at year 430 (when the simulation test begins), and then subsequently when a new survey estimate becomes available. Assessment of whether the simulation achieves conservation objectives occurs after 100 years at year 530. To keep the illustration simple, this example does not include any uncertainty in the bycatch.

3.4 Simulation tests

As a basis for the simulation testing, a "base case" was established with the following conditions:

- Maximum net productivity of either 2% or 4% of population size;
- Initial depletion of 50% K;
- Survey abundance estimates available every 6 years;
- Uncertainty in estimates of removals (bycatch) given by a CV of 0.4;
- Constant carrying capacity, K;
- No catastrophic episodic events.

The population model was run under these conditions (two scenarios – one for each value of the maximum net productivity) for a range of values of γ (0.5, 1, 1.5, 2, 2.5, 3) to determine the greatest value of γ that allowed the conservation objectives to be met, a process known as tuning.

Then, using the value of γ determined from the tuning of the base case, a series of simulations was conducted to test the performance of the RLA to various sources of uncertainty (equivalent to failures of the assumptions made in the base case). These tests included:

- A different level of initial depletion at the onset of management (60-90% K) – note that these tests are "easier" than the depletion of 50% assumed by the base case;
- A higher level of uncertainty in removals (bycatch) estimates (CV = 0.6);
- Environmental degradation (carrying capacity, K, declining by 50% over 100 years);
- Episodic catastrophic events, such as epizootics, that reduce the population by 50% with annual probability of 0.02, i.e. on average every 50 years. This simulation test had technical issues and the results are not reported.

The principle is that the RLA should be robust to plausible levels of uncertainty. If the results of a simulation test indicate that the variation in performance compared to the base case may compromise its robustness, this would need to be taken into account in how the results are used. This might include running simulation tests with different values of the tuning parameter.

3.5 Performance metrics

Performance metrics used to illustrate results and to determine how well the RLA met conservation objectives included:

- Plot of the 100 simulated population trajectories over 100 years;
- Plot of animals removed (as determined by the RLA) over 100 years;
- 5^{th}, 50^{th} (median) and 95^{th} percentiles of final depletion;
- 5^{th}, 50^{th} (median) and 95^{th} percentiles of minimum depletion;
- Average annual number of animals removed in the final 12 years;
- Relative recovery rate (depletion with removals set by the RLA vs depletion with removals set to zero).

4. RESULTS OF SIMULATION TESTING

Performance metrics for the results of the simulation tests are given in Appendix 1.

4.1 Base case simulations

Results of the base case simulations (Appendix 1, sections 1.1 and 2.1) indicated that appropriate values of γ were 1.0 if true maximum net productivity (MNP) were 2%, and 2.5 if true maximum net productivity were 4%. For these values, the median final depletion after 100 years of managing bycatch was 80%, as required to meet the conservation objective (Appendix 1, sections 1.1.2 and 2.1.3). However, despite meeting the conservation objective, performance of the RLA with MNP = 4% and γ = 2.5 was rather variable (Appendix 1, section 2.1.3). A case could perhaps be made that a smaller γ should be selected for MNP = 4%. The parameter γ acts as a simple multiplier in the removals calculation (section 3.2.2). The higher value of γ determined for MNP = 4% than for MNP = 2% allows more animals to be removed because a faster growing population can recover from these removals more quickly.

4.2 Different starting depletion levels

As expected, the results of the simulation tests for levels of starting depletion that were less severe than the base case (60%, 70%, 80% and 90% vs 50% of carrying capacity for the base case) showed that the conservation objective was equally or more likely to be met than for the base case (Appendix 1, sections 1.2 and 2.2). In the plots for these simulations for MNP = 2%, a green line shows the trajectory of the population with no removals, for comparison.

4.3 Decrease in carrying capacity

The simulations in which carrying capacity decreased to 50% over the 100 year period of the simulation showed slightly better performance than the base case for MNP = 2% (Appendix 1, section 1.3) and slightly worse performance than the base case for MNP = 4% (Appendix 1, section 2.3). The improved performance of the RLA applied to a population with MNP = 2% (Appendix 1, section 1.3) may be because once a simulated population has recovered above 80% of K, it responds relatively slowly to the decline in carrying capacity. For MNP = 4%, the performance of the RLA was rather variable with a median depletion after 100 years of 0.71, somewhat below the conservation objective (Appendix 1, section 2.3). Depending on how plausible this modelled scenario is considered to be, this result might warrant further consideration, possibly including additional simulations.

4.4 Increase in bycatch uncertainty

The simulations in which bycatch uncertainty was increased from a CV of 0.4 to a CV of 0.6, showed slightly reduced performance for both MNP = 2% and MNP = 4% (Appendix 1, sections 1.4 and 2.4). For MNP=2%, performance was rather consistent with a median final depletion of 0.77. For MNP = 4%, performance was much more variable but the median final depletion of 0.76 was still close to the conservation objective.

4.5 Summary of simulation results

Overall, the results show that the RLA with $\gamma = 1$ is rather robust to the uncertainties included in the simulation testing. Results for the RLA with $\gamma = 2.5$ were more variable and not as robust. At present, therefore, a conservative approach could be to consider the RLA with $\gamma = 1$ as an appropriate procedure for implementation.

5. IMPLEMENTATION OF THE RLA

The developed RLA was implemented using a time series of bycatch of harbour porpoise in the North Sea (area defined by the ICES North Sea Management Unit [ICES 2013]) and estimates of abundance for this area from the three SCANS surveys in 1994, 2005 and 2016 to estimate depletion at the time of the most recent survey (2016) and the value of the growth parameter, μ.

Based on the results of the simulation tests, a value of $\gamma = 1$ was used to implement the removals calculation. A value of $\gamma = 2.5$ was also used to illustrate the difference in results.

The R code to implement the RLA is given in Appendix 2.

5.1 Historical bycatch series

The bycatch series used to estimate initial depletion was created from available information on fishing effort and bycatch rates from a number of sources. The aim was first to create a time series of fishing effort (days at sea) for the fleets of the main countries fishing gear that could entangle harbour porpoise (gillnets, drift nets, tangle nets) operating in the North Sea (Belgium, Denmark, England, France, Germany, Netherlands and Scotland), and then to use typical levels of estimated harbour porpoise bycatch rate to estimate the number of porpoises that were bycaught in each year.

The primary source of fishing effort data was a time series from 1966 to 2015 of estimated days at sea by English vessels fishing gear that could entangle harbour porpoise - gillnets, drift nets, tangle nets (S.P. Northridge pers. comm.). Equivalent data were available for Denmark from 1990 to 2000 (S.P. Northridge pers. comm.).

Estimates of days at sea for 2003-2015 for fleets operating in the North Sea other than the English fleet were obtained using data from the STECF database (https://stecf.jrc.ec.europa.eu/dd/effort). For each of the non-English fleets, in the absence of other information, a multiplier relative to the English fleet was calculated for each year and applied to the English days at sea.

For 1966-2002 for non-English fleets other than Denmark, days at sea were estimated using the mean multiplier from the STECF data for 2003-2015. For 1966-1989 for the Danish fleet, days at sea were assumed equal to the English fleet (the average multiplier in the early 1990s was approximately 1). Multipliers for the Danish fleet for 2001 and 2002 were interpolated between 2000 and 2003.

Three overall estimated bycatch rates were used to calculate a plausible range of estimated total annual bycatch from total annual estimated days at sea: 1 porpoise every 5 days at sea (high); 1 porpoise every 10 days at sea (medium); and 1 porpoise every 20 days at sea (low). These overall bycatch rates were based on data from S.P. Northridge (pers. comm.) The bycatch series generated for 1966 to 2015 are given in Appendix 3.

In the implementation presented here, the bycatch time series generated from the high bycatch rate has been used.

5.2 Estimates of abundance

Estimates of harbour porpoise abundance for the ICES North Sea Assessment Unit area were available for 1994, 2005 and 2016 (Hammond et al. 2017). These were: 289,150, 355,408 and 345,373, with CVs of 0.14, 0.22, and 0.18, respectively. The estimates for 1994 and 2005 result from reanalyses of SCANS and SCANS-II data to ensure consistency with the 2016 estimate (see Hammond et al. 2017).

5.3 Results

To ensure representative results, the RLA was implemented 10 times and the average values of the estimated parameters taken.

Typical posterior distributions of: estimated depletion at the time of the final survey (2016); the carrying capacity derived from this; and the growth parameter, μ are shown in Figure 3.

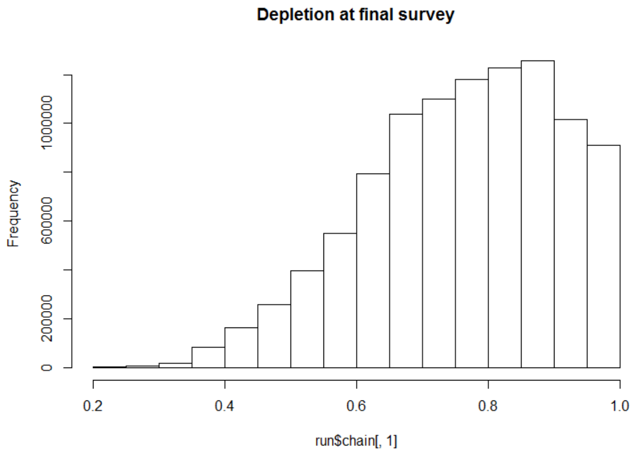
The posterior distributions show little support for the population of harbour porpoises in the North Sea being heavily depleted or for the current carrying capacity being less than 350,000 animals. The almost uniform posterior distribution of the growth parameter shows that the available data are unable to improve on the assumed prior distribution and the estimated value (median) is halfway between the limits placed on the prior.

Median values of the estimated parameters were:

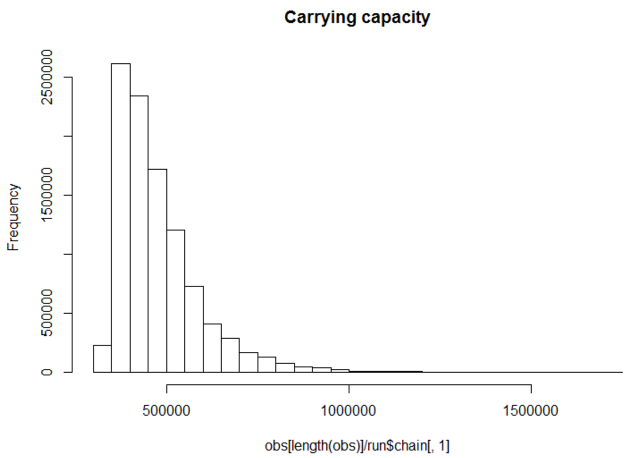
- Depletion in 2016 = 0.76
- Derived carrying capacity in 2016 = 458,000
- Growth parameter = 0.025

With $\gamma = 1$ in the removals calculation, the removals limit was 1,856 animals per year for a six-year period until a new survey estimate is assumed to become available in 2022, at which point the RLA would be implemented again with this estimate and including bycatch estimates for 2016-2021. For comparison, with $\gamma = 2.5$, the removals limit was 4,641 per year.

(a)



(b)



(c)

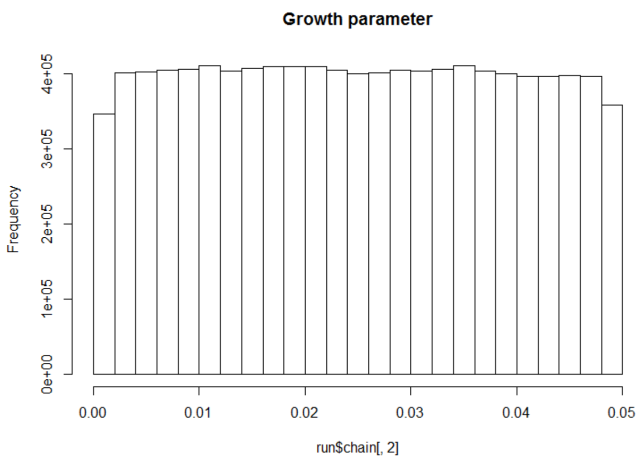


Figure 3. Posterior distributions of: (a) estimated depletion at the time of the final survey (2016); (b) the carrying capacity derived from estimated depletion and the final abundance estimate; (c) the growth parameter, μ.

6. DISCUSSION

6.1 Results presented

The work achieved so far on developing a Removals Limit Algorithm and its example implementation for harbour porpoises in the North Sea comes with a considerable number of assumptions and caveats (see below). Nevertheless, the results provide some indication of the level of current depletion of the harbour porpoise population in the North Sea (around 75% of pre-bycatch population size) and the level of annual anthropogenic mortality that the population might be able to sustain and still meet the specified conservation objective (around 1,800 animals). The calculated removal level is around half of one percent of current population size. This level of annual mortality is similar to that generated by implementations of the IWC's CLA, which is perhaps not surprising given the similarity between the RLA and the CLA.

However, it is much smaller than the 1.7% of population size currently adopted by ASCOBANS, OSPAR and the European Commission. The disparity is partly because the RLA calculates more "conservative" removal limits to ensure that it is robust to the uncertainties tested through simulation. It is also partly because the tuning level chosen represented a maximum net productivity (MNP) of 2% per year ($\gamma = 1$), rather than the 4% used to generate the 1.7% bycatch limit. If the RLA were used with a tuning level representing MNP = 4% ($\gamma = 2.5$), our results give an annual bycatch of around 1.3% of population size, although results of the simulation tests were less than satisfactory for this level of tuning. A MNP of at least 4% is likely for harbour porpoise populations (Woodley & Read 2011; Caswell et al. 2008), so it may be useful to rerun the simulation trials using a tuning of $\gamma = 1.5$ or 2 to see if RLA performance improves over using $\gamma = 2.5$.

6.2 Data requirements

The RLA is initiated with a starting depletion level and at least one estimate of abundance. The starting depletion level could be estimated using historical removals data (as in our simulations and example implementation) or a value could be provided. Subsequently, minimum data requirements are estimates of annual removals (bycatch in our example implementation) and estimates of abundance every 6 years.

Estimation of bycatch is challenging. It requires data on fishing effort from relevant fleets and on bycatch rates per unit of fishing effort. As described above (section 5.1), fishing effort information is incomplete and while that remains the case, any estimates of bycatch from available data will likely be negatively biased. Estimates of bycatch rates are available but, as also described above, they come from a limited number of studies that generated highly variable results.

In our example implementation of the RLA for harbour porpoise in the North Sea we generated an annual removals limit applicable to the next six years. In a real implementation, after six years, another estimate of abundance would be available, estimates of bycatch would be provided for the six previous years, and the RLA would be refitted. If the estimates of bycatch are negatively biased, the RLA would tend to over-estimate depletion (i.e. estimate it as a higher proportion of carry capacity than it should be) and to set removals limits that were too high. Over time this would be somewhat compensated by estimates of abundance that reflected true population size but the overall effect would remain. If true bycatch were greater than the removals limits but negatively biased estimates provided were smaller than the limits, conservation objectives would likely not be achieved.

Future work could explore incorporation of the impact on RLA performance of bias in estimates of future bycatch leading to the determination of an alternative level of tuning. The challenge would be to select levels of bias that were plausible. A practical solution could be to determine appropriate tunings for a range of assumed bias in bycatch estimates, with a view to deciding which level of bias was realistic for a real implementation. This could include consideration of biases in fishing effort data and in estimates of bycatch rate, separately. Results from these simulation tests could also be used to put demands on the quality of bycatch data acceptable for implementation.

6.3 Additional assumptions

Our results are dependent on the appropriateness of the population model as a suitable test bed, the definition of the base case simulation and the simulations to test the performance of the RLA to violations in the assumptions made in the base case. All of these could be formulated differently, which would alter the results. If any factors that had not been considered in simulation tests were of particular concern in a proposed implementation, these would need to be considered as additional simulation trials to ensure robustness of the RLA.

6.4 Population structure

The IWC's RMP includes additional "multi-stock rules", which determine how catch limits generated by the CLA are to be distributed spatially based on knowledge of population structuring. This is because if there is population structure (incomplete mixing of animals between different areas) and anthropogenic activities are managed without taking this into account so that removals may be concentrated in particular areas, there is a potential danger of depletion of "local" populations.

The current advice from ICES is that there is a single "Management Unit" (MU) for harbour porpoise in the North Sea (ICES 2013). However, there has been considerable discussion about whether genetic differences among animals in this area might warrant the delineation of more than one MU (e.g. Evans & Teilmann 2009; ICES 2012). ICES (2013) recommended that this be explored as part of work to develop models to set limits to bycatch to meet specified conservation objectives. This was explored to some extent by Winship (2009) but there has been insufficient time in the current project to pursue this. Adding population structure to the current RLA will therefore require additional development.

6.5 Conservation objectives and management

All our results are also entirely dependent on the quantitative definition of the conservation objective used. If a different conservation objective were selected, a new set of simulations would be required to ensure that the developed RLA generated removal limits that met the new conservation objective. For example, an alternative way to define the ASCOBANS interim objective could be that a population should recover to or be maintained at 80% of carrying capacity within a given period, 95% of the time (Winship 2009; ICES 2013). This would result in smaller bycatch limits and the population being maintained at a higher percentage of carrying capacity on average; 85-90% based on previous equivalent work (Winship 2009). For comparison, the PBR procedure (Wade 1998) was developed to achieve the conservation objective that a population should recover to or be maintained at 50% of carrying capacity within 100 years, 95% of the time.

More generally, managers would need to determine how the results of any RLA implementation are used in practice. For example, the aim of ASCOBANS is ultimately to reduce bycatch to zero, or at least levels approaching zero, but current mitigation is unable to guarantee near-zero bycatch in fishing gear and it is possible that this might always be the case. The RLA is intended as a tool to provide useful information in this context.

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Appendix 1

Results of the simulation tests of RLA performance

Results are given for:

1. Base case simulations to determine the appropriate value of the tuning parameter, γ;

The base case is defined as:

- Maximum net productivity (MNP) = 2% or 4%;
- Initial depletion of 50% of K;
- Survey abundance estimates available every 6 years;
- Uncertainty in bycatch estimates given by a CV of 0.4;
- Carrying capacity assumed not to change;
- No catastrophic episodic events.

For the selected value of γ for each of MNP = 2% and MNP = 4%:

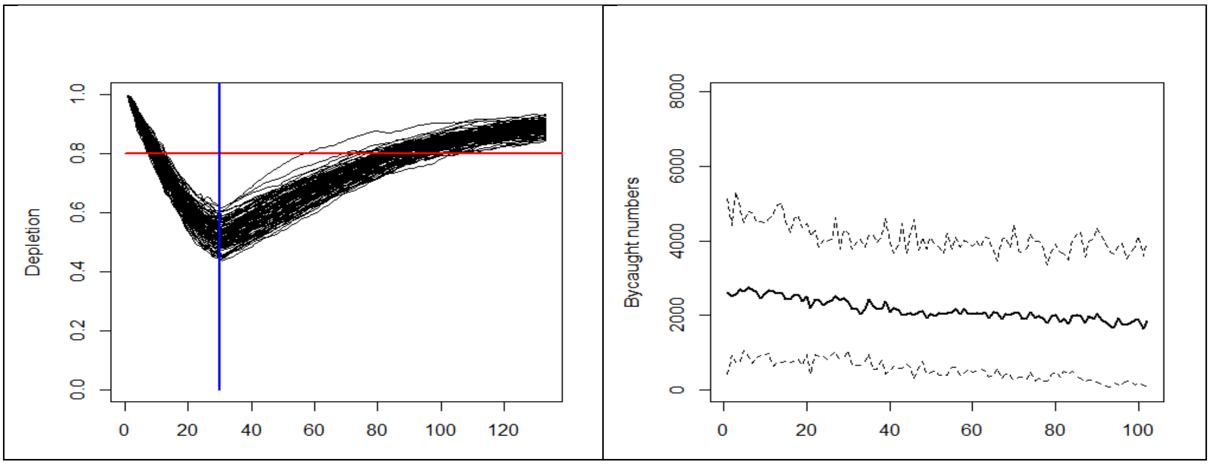
2. Simulations with different levels of starting depletion (60%, 70%, 80%, 90% of K);
3. A simulation with carrying capacity decreasing to 50% over 100 years;
4. A simulation with bycatch uncertainty given by a CV of 0.6.

The simulation with a catastrophic event occurring at an annual probability of 0.02 with the effect of reducing population size by 50% had technical problems and could not be implemented.

1. Maximum net productivity = 2%

1.1 Base case simulations with varying tuning parameter γ

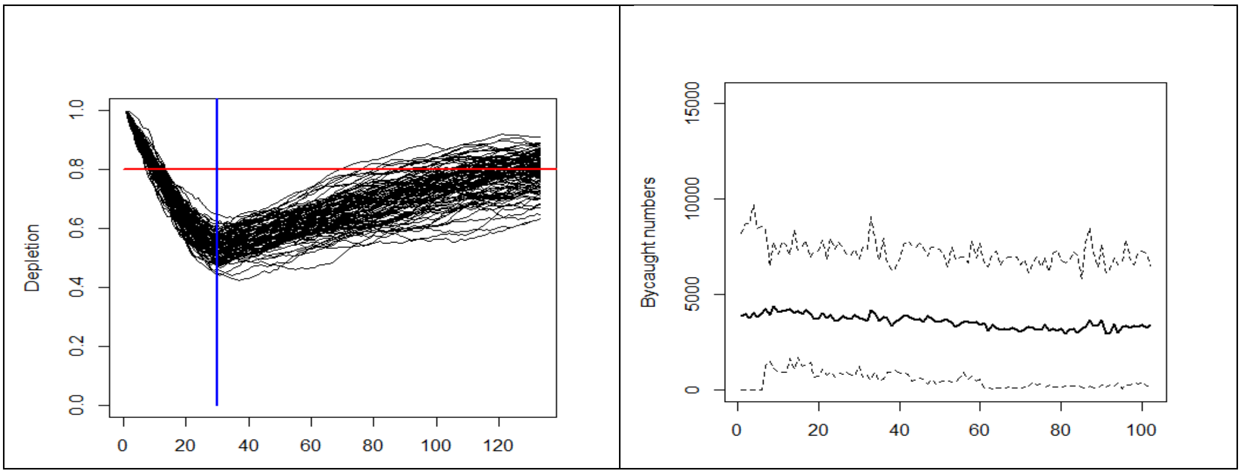
1.1.1 γ = 0.5



MNP = 2%; γ = 0.5	**5th %-ile**	**Median**	**95th %-ile**
Final depletion after 100 years	0.85	0.89	0.92
Minimum observed depletion	0.45	0.52	0.59

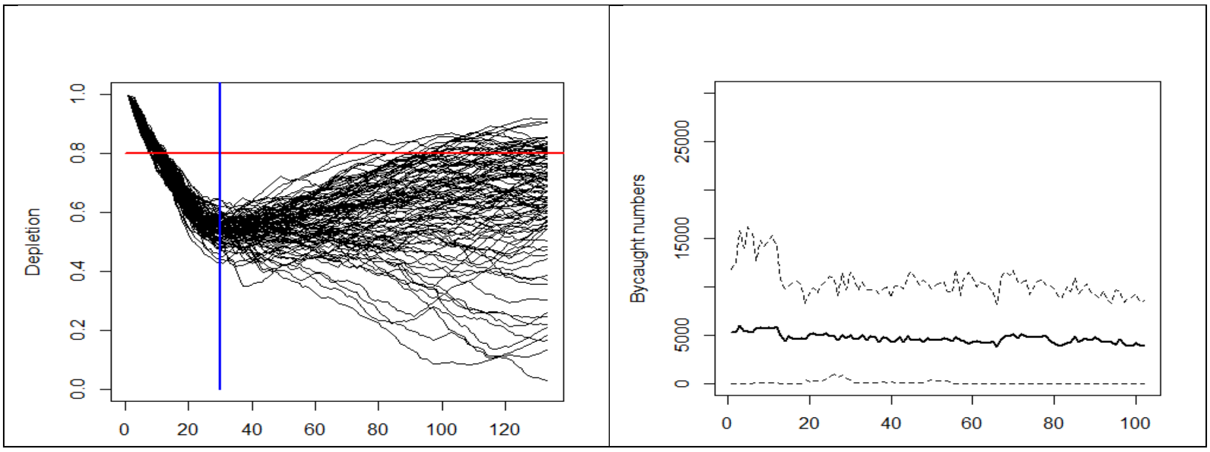
Average annual removals over final 12 years	592	1,744	2,937

1.1.2 $\gamma = 1.0$



MNP = 2%; $\gamma = 1.0$	**5th %-ile**	**Median**	**95th %-ile**
Final depletion after 100 years	0.68	0.80	0.88
Minimum observed depletion	0.47	0.53	0.60
Average annual removals over final 12 years	1,108	3,319	5,051

1.1.3 $\gamma = 1.5$

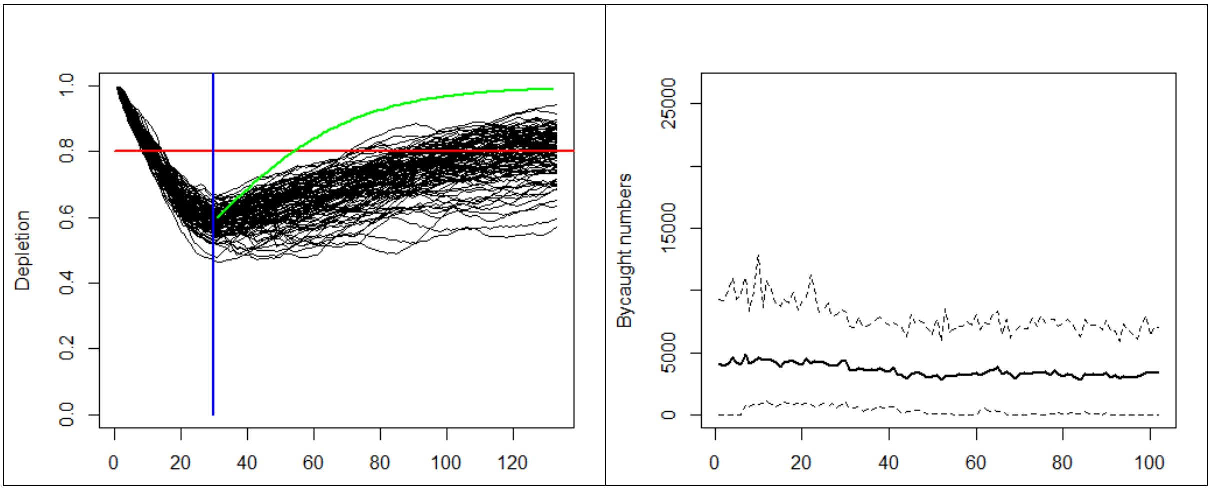


MNP = 2%; $\gamma = 1.5$	**5th %-ile**	**Median**	**95th %-ile**
Final depletion after 100 years	0.21	0.67	0.85

Minimum observed depletion	0.16	0.49	0.56
Average annual removals over final 12 years	1,226	4,403	6,815

1.2 Simulations with different initial depletions; $\gamma = 1.0$

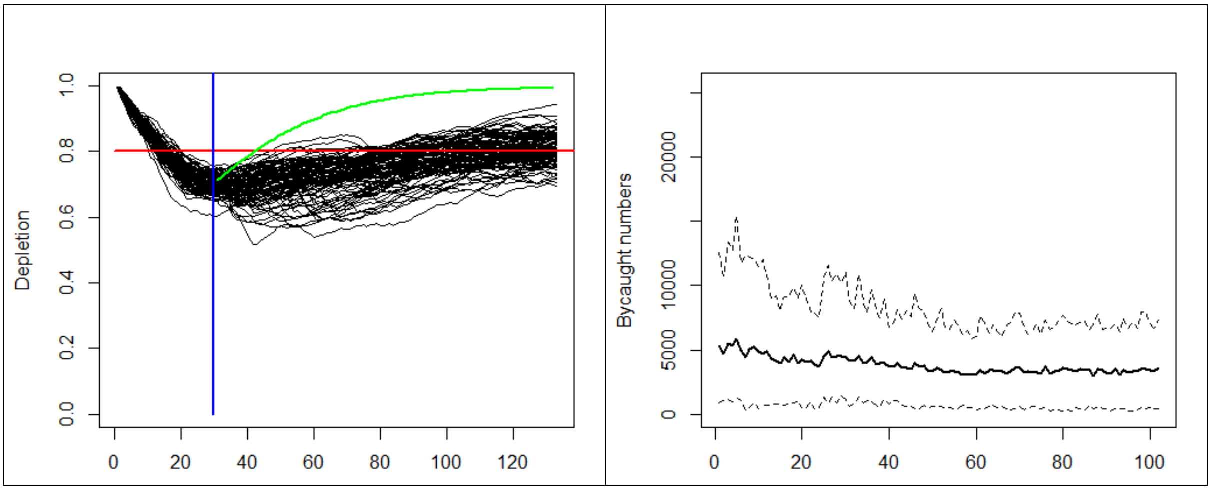
<u>Initial depletion = 60% of K</u>



The green curve is the population trajectory with zero bycatch.

MNP = 2%; $\gamma = 1.0$	**5^{th} %-ile**	**Median**	**95^{th} %-ile**
Final depletion after 100 years	0.69	0.82	0.88
Minimum observed depletion	0.49	0.58	0.63
Average annual removals over final 12 years	255	3,201	4,908

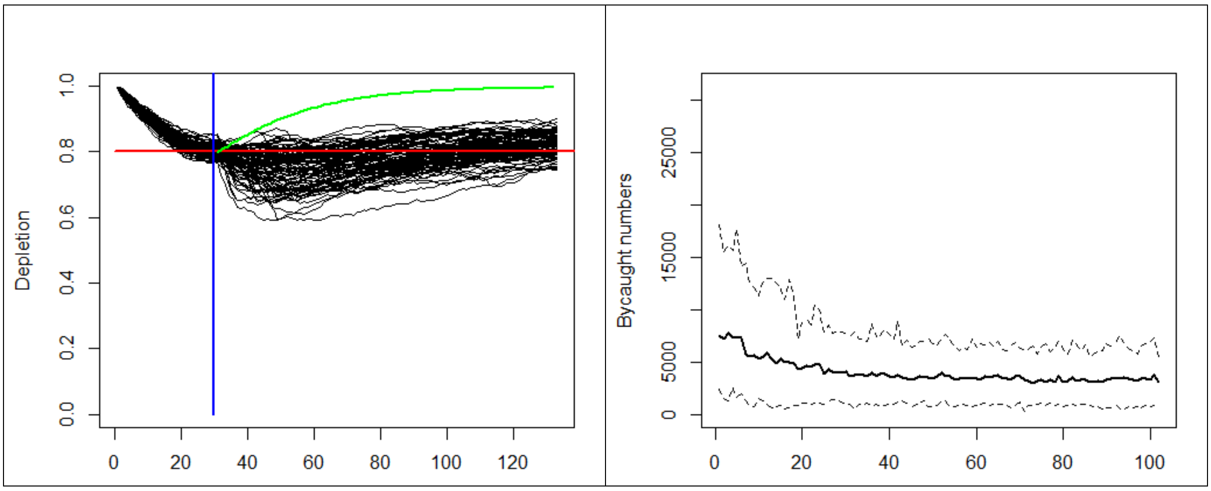
Initial depletion = 70% of K



The green curve is the population trajectory with zero bycatch.

MNP = 2%; γ = 1.0	**5th %-ile**	**Median**	**95th %-ile**
Final depletion after 100 years	0.73	0.81	0.88
Minimum observed depletion	0.58	0.67	0.73
Average annual removals over final 12 years	1,534	3,349	5,102

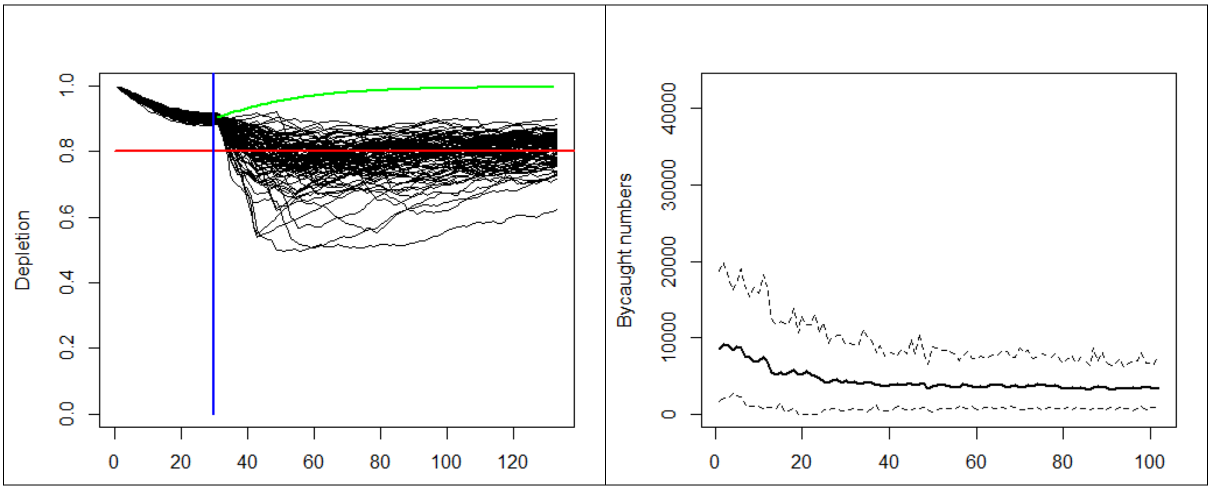
Initial depletion = 80% of K



The green curve is the population trajectory with zero bycatch.

MNP = 2%; γ = 1.0	**5th %-ile**	**Median**	**95th %-ile**
Final depletion after 100 years	0.76	0.82	0.87
Minimum observed depletion	0.64	0.73	0.79
Average annual removals over final 12 years	1,856	3,464	5,041

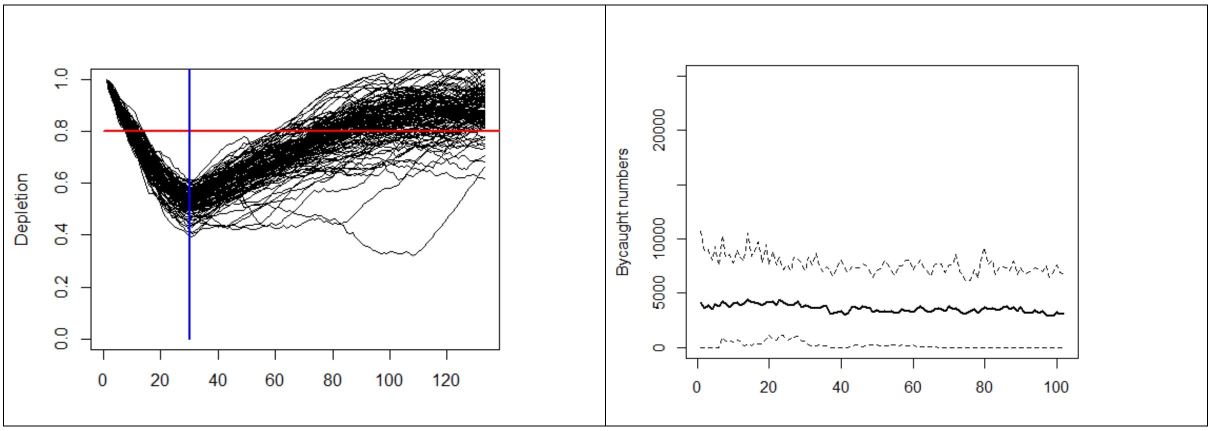
Initial depletion = 90% of K



The green curve is the population trajectory with zero bycatch.

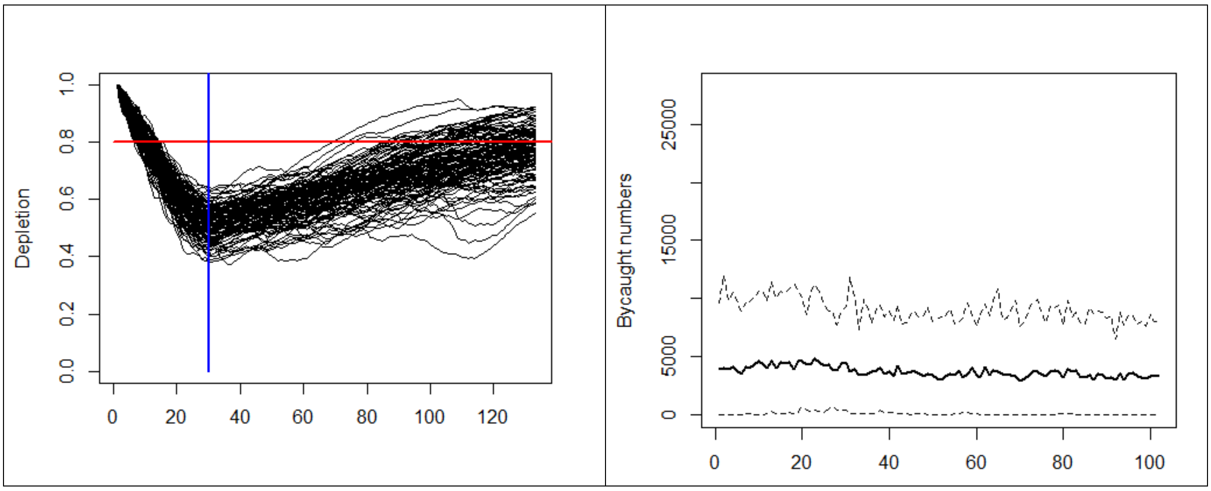
MNP = 2%; $\gamma = 1.0$	5th %-ile	Median	95th %-ile
Final depletion after 100 years	0.73	0.82	0.86
Minimum observed depletion	0.55	0.75	0.81
Average annual removals over final 12 years	1,685	3,434	5,011

1.3 Carrying capacity decreasing to 50% over 100 years; $\gamma = 1.0$



MNP = 2%; $\gamma = 1.0$	5th %-ile	Median	95th %-ile
Final depletion after 100 years	0.74	0.89	1.04
Minimum observed depletion	0.43	0.53	0.59
Average annual removals over final 12 years	280	3,310	5,038

1.4 Bycatch uncertainty CV = 0.6; γ = 1.0

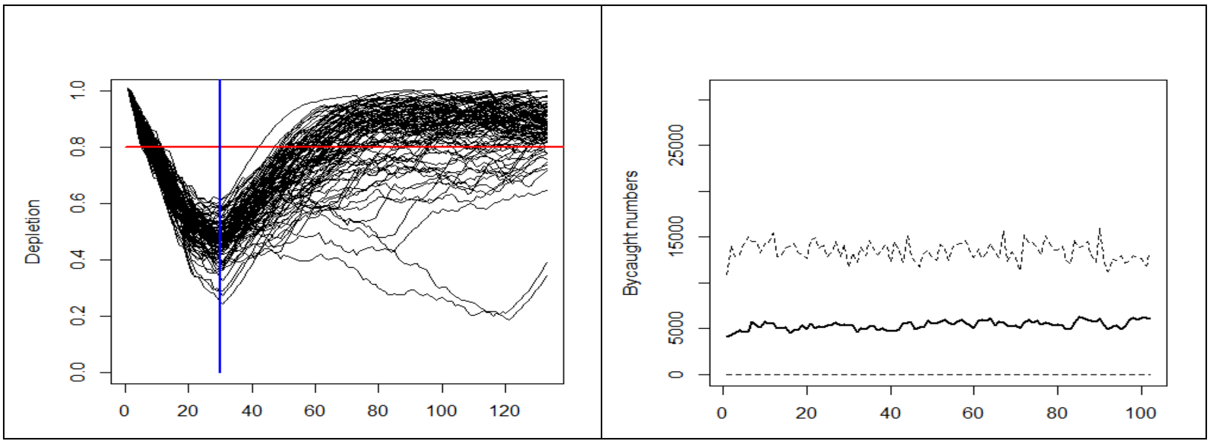


MNP = 2%; γ = 1.0	**5th %-ile**	**Median**	**95th %-ile**
Final depletion after 100 years	0.62	0.77	0.89
Minimum observed depletion	0.43	0.51	0.59
Average annual removals over final 12 years	197	3,697	5,704

2. Maximum net productivity = 4%

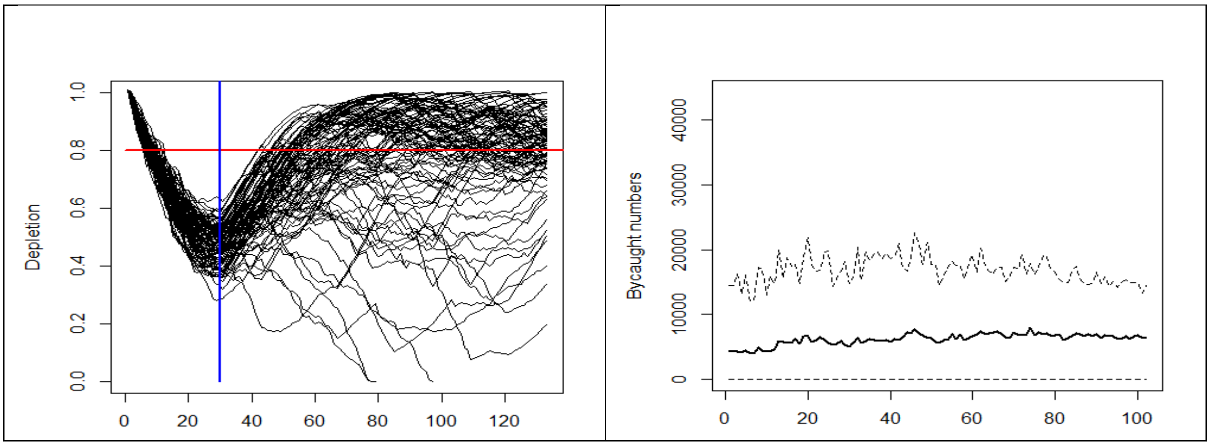
2.1 Base case simulations with varying tuning parameter γ

<u>2.1.1 γ = 1.5</u>



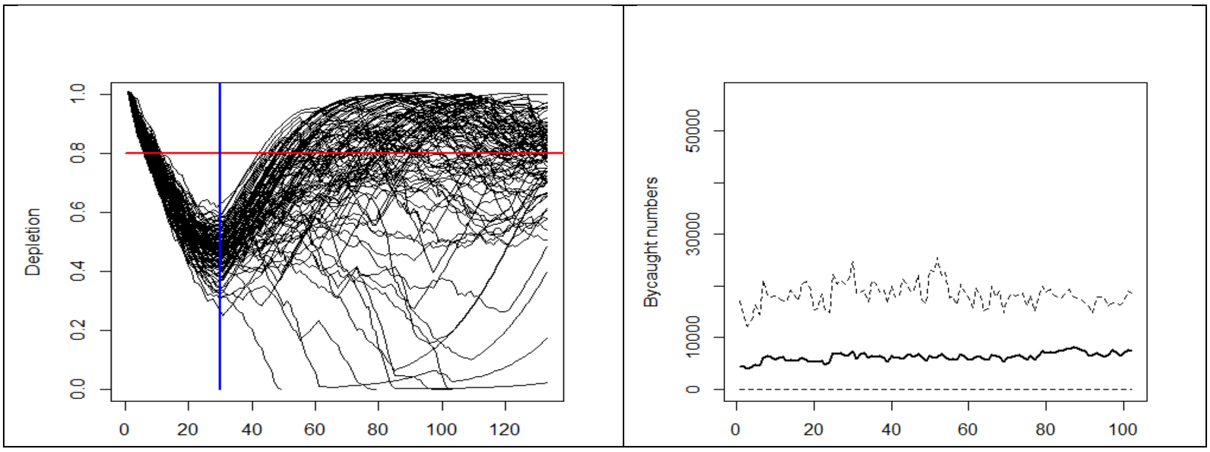
MNP = 4%; γ = 1.5	5th %-ile	Median	95th %-ile
Final depletion after 100 years	0.72	0.87	0.96
Minimum observed depletion	0.33	0.47	0.57
Average annual removals over final 12 years	576	6,047	9,429

<u>2.1.2 γ = 2.0</u>



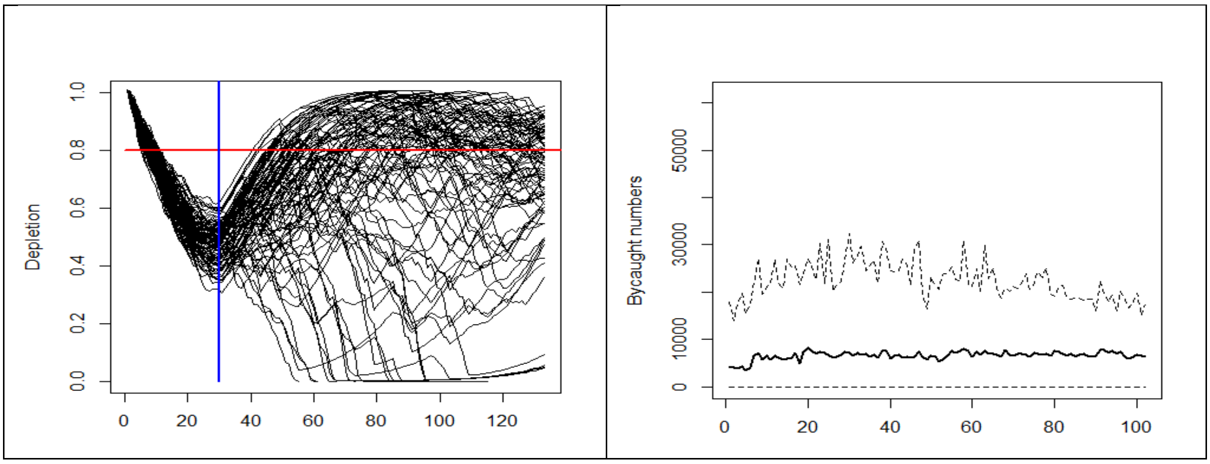
MNP = 4%; γ = 2.0	5th %-ile	Median	95th %-ile
Final depletion after 100 years	0.34	0.82	0.97
Minimum observed depletion	0.10	0.45	0.56
Average annual removals over final 12 years	0	6,863	11,652

2.1.3 γ = 2.5



MNP = 4%; $\gamma = 2.5$	**5th %-ile**	**Median**	**95th %-ile**
Final depletion after 100 years	0.02	0.80	0.95th
Minimum observed depletion	0	0.46	0.55
Average annual removals over final 12 years	0	7,278	13,052

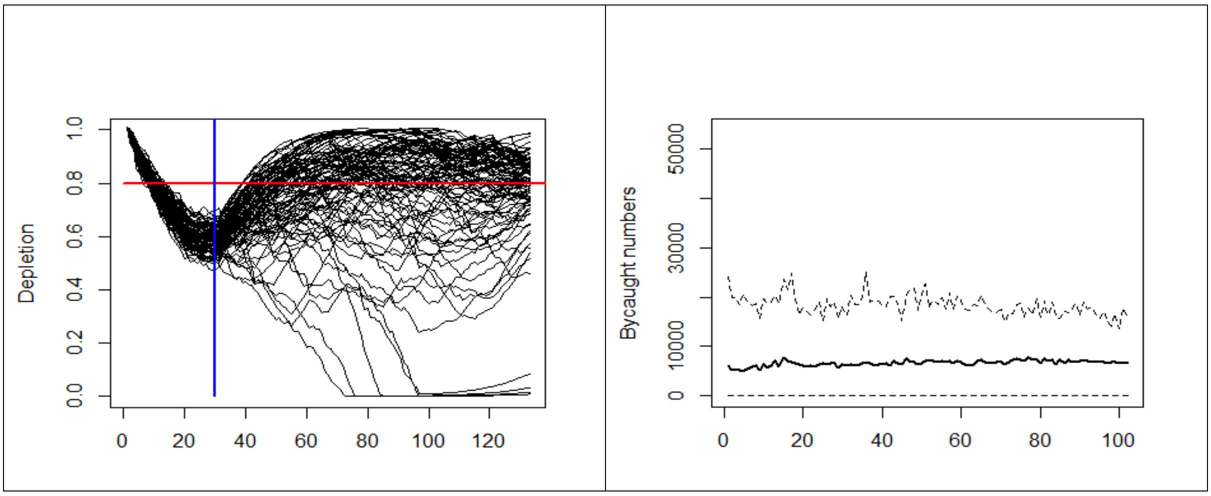
2.1.4 γ = 3.0



MNP = 4%; $\gamma = 3.0$	**5th %-ile**	**Median**	**95th %-ile**
Final depletion after 100 years	0	0.75	0.92
Minimum observed depletion	0	0.43	0.53
Average annual removals over final 12 years	0	7,051	14,845

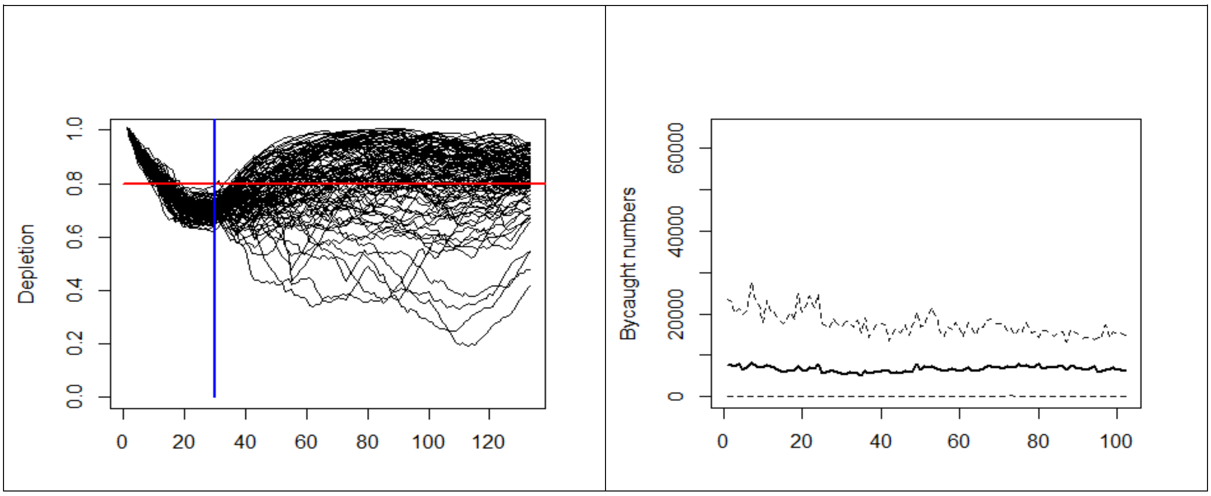
2.2 Simulations with different initial depletions; $\gamma = 2.5$

2.2.1 Initial depletion = 60% of K



MNP = 4%; $\gamma = 2.5$	5th %-ile	Median	95th %-ile
Final depletion after 100 years	0.089	0.82	0.93
Minimum observed depletion	0.01	0.55	0.63
Average annual removals over final 12 years	0	7,251	12,575

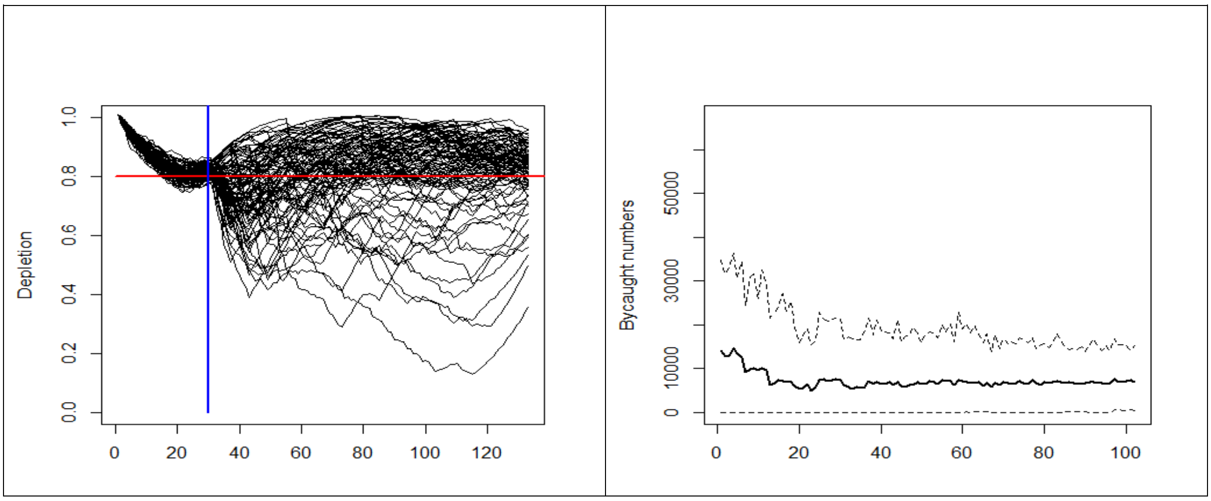
2.2.2 Initial depletion = 70% of K



MNP = 4%; $\gamma = 2.5$	5th %-ile	Median	95th %-ile
Final depletion after 100 years	0.65	0.84	0.94
Minimum observed depletion	0.35	0.66	0.72

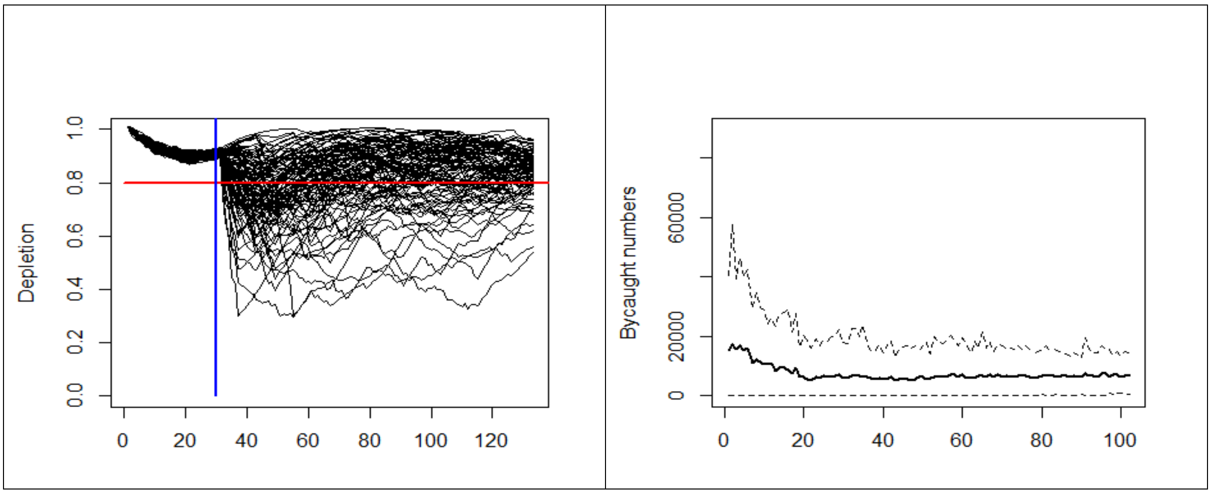
Average annual removals over final 12 years	2,379	6,511	11,471

2.2.3 Initial depletion = 80% of K



MNP = 4%; $\gamma = 2.5$	**5^{th} %-ile**	**Median**	**95^{th} %-ile**
Final depletion after 100 years	0.59	0.84	0.93
Minimum observed depletion	0.39	0.70	0.80
Average annual removals over final 12 years	2,258	6,977	11,526

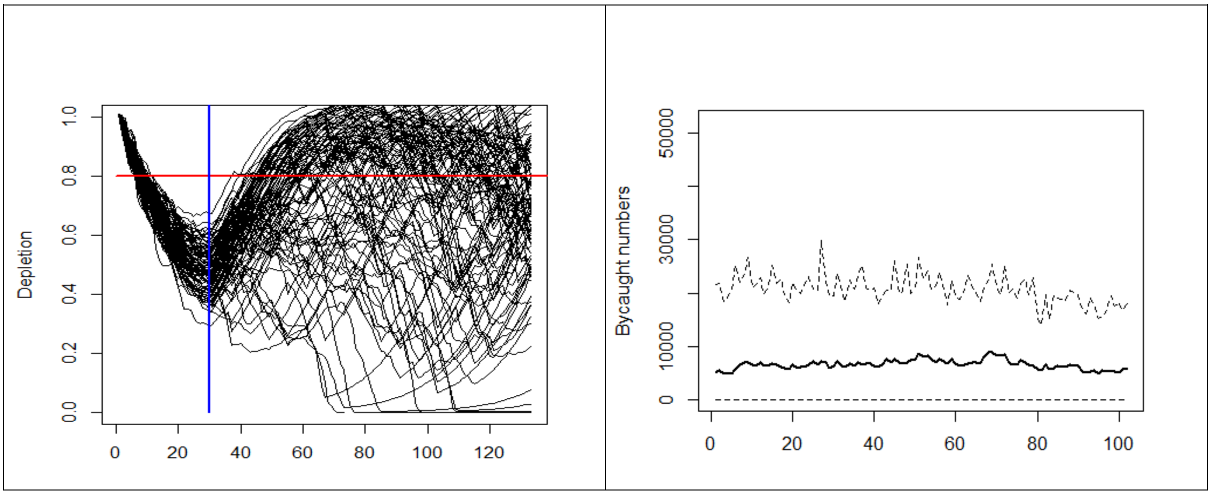
2.2.4 Initial depletion = 90% of K



MNP = 4%; $\gamma = 2.5$	**5^{th} %-ile**	**Median**	**95^{th} %-ile**

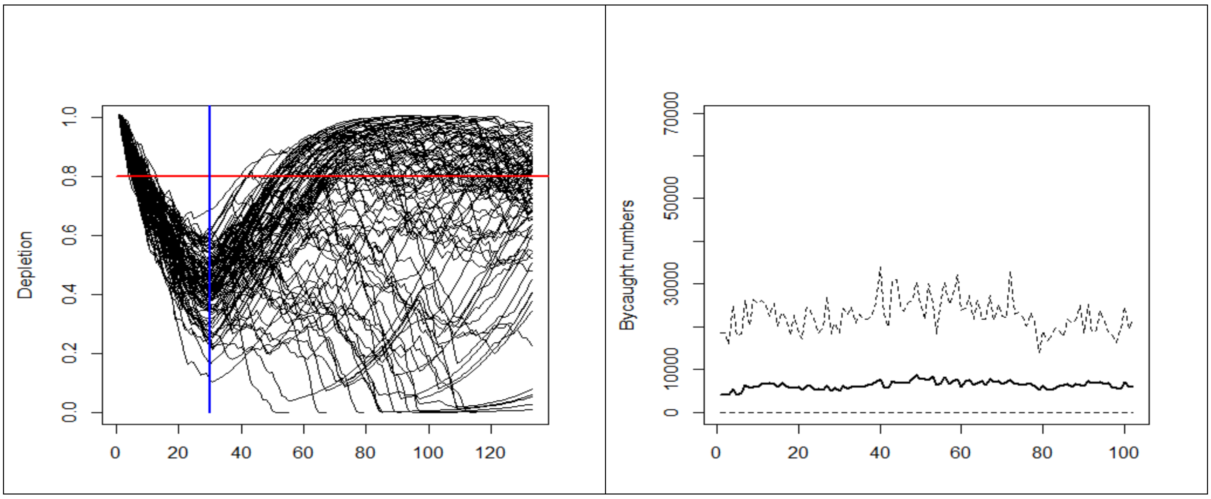
Final depletion after 100 years	0.69	0.85	0.94
Minimum observed depletion	0.40	0.70	0.87
Average annual removals over final 12 years	2,677	7,057	11,900

2.3 Carrying capacity decreasing to 50% over 100 years; $\gamma = 2.5$



MNP = 4%; $\gamma = 2.5$	5th %-ile	Median	95th %-ile
Final depletion after 100 years	0.03	0.71	1.04
Minimum observed depletion	0	0.53	0.91
Average annual removals over final 12 years	0	4,363	13,561

2.4 Bycatch uncertainty CV = 0.6; $\gamma = 2.5$



MNP = 4%; γ = 2.5	**5^{th} %-ile**	**Median**	**95^{th} %-ile**
Final depletion after 100 years	0	0.76	0.95th
Minimum observed depletion	0	0.35	0.56
Average annual removals over final 12 years	0	6,716	13,350

Appendix 2

R code used to implement the RLA

```
#
##################################################################################
###### Code to implement the RLA for harbour porpoise in the North Sea #######
##################################################################################
#
require(truncnorm)
#
## Input data
#
obs = c(289150,355408,345373) ## SCANS survey abundance estimates
CVs = c(0.14,0.22,0.18) ## SCANS survey CV estimates
#
byc.series = read.csv(file.choose(), header=TRUE)
byc.series = byc.series[byc.series$year<2016,]
bycatch.years = 1966:byc.series[length(byc.series$year),1]
byc = c(byc.series$hi) ## select bycatch series to use
name.byc = "high bycatch"
#
#bycatch.years = 1966:2015
#byc = rep(0,50)
#name.byc = "zero bycatch"
#
idx = c(which(bycatch.years%in%c(1994,2005)),length(bycatch.years)+1) ## index of bycatch years
where we have a survey
#
## Transform for lognormal likelihood
#
sd_scale=sqrt(log((CVs)^2+1))
mean_scale=log(obs)-.5*log((CVs)^2+1)
#
##################################################
###### Functions to fit the Bayesian RLA #######
##################################################
#
Fit.RLA <- function(parame){
  DT = parame[1]
  mu = parame[2]
  #bias = parame[3]
  bias=1
  carry=obs[length(obs)]/DT # the population begins at carrying capacity
  est=rep(NA,length(byc)+1)
  est[1]=carry
  for(i in 2:length(byc)){
    est[i]=max(est[i-1]-byc[i-1]+1.4184*mu*est[i-1]*(1-(est[i-1]/carry)^2),0.1,na.rm=T)
  }

log.lik.lognorm=sum(dlnorm(x=est[idx]*bias,meanlog=mean_scale,sdlog=sd_scale,log=T),na.rm=T)
  return(list(lik=log.lik.lognorm))
}
```

```
#
MCMC_metrop.proposal <- function(start.val, iterations){
  chain = array(dim = c(iterations+1,3))
  chain[1,] = start.val
  for (i in 1:iterations){
    propos = proposal(chain[i,])
    while(any(c(propos<0 ,propos>c(1,.05,5/3)))){propos = proposal(chain[i,])} # all new values must
be inside distribution
    #acceptance.probab = exp(posterior(propos)[1] - posterior(chain[i,])[1]) ## raw likelihood
    acceptance.probab = exp(posterior(propos)[1]/16 - posterior(chain[i,])[1]/16) ### weighted
likelihood
    if (runif(1) < acceptance.probab){chain[i+1,] = c(propos)}
    else{chain[i+1,] = c(chain[i,])}
  }
  return(chain=list(chain=chain))
}
#
prior.lik <- function(parame){
  DT = parame[1]
  mu = parame[2]
  bias = parame[3]
  DT.prior = dunif(DT, min=0.0001, max=1, log = T) ## in log
  mu.prior = dunif(mu, min = 0.0001, max=.05, log = T) ## in log
  bias.prior = dunif(bias, min=0, max=5/3, log = T) ## in log
    return(DT.prior + mu.prior + bias.prior) ## in log
}
#
posterior <- function(parame){return (Fit.RLA(parame)$lik + prior.lik(parame))}
#
## To reject any proposals that fall outside distribution
#
proposal <- function(parame){
  #return(c(rnorm(3,mean = parame, sd= c(0.002,0.0005,.005)))) ###  check sensitivity of these
transition sd
  return(c(rtruncnorm(1, a=0, b=1, mean = parame[1], sd = 0.001), ## Depletion
           rtruncnorm(1, a=0, b=0.05, mean = parame[2], sd = 0.0005), ## mu (grow param)
           rtruncnorm(1, a=0, b=5/3, mean = parame[3], sd = 0.005))) ## bias parameter
}
#
################################
###### Implement the RLA #######
################################
#
start.val = c(0.5,0.025,0.5)
number_of_iterations = 10000000
burn_in = 1000000
#
run = MCMC_metrop.proposal(start.val, number_of_iterations)
select=seq(burn_in,length(run$chain[,1]),by=number_of_iterations/3000)
#
## Plots of posterior distributions
#
par(mfrow=c(2,2))
hist(obs[length(obs)]/run$chain[,1],main="Carrying capacity",xlab="Population size")
hist(run$chain[,1],main="Depletion at final survey",xlab="Proportion of carrying capacity")
```

```
hist(run$chain[,2],main="Growth parameter",xlab="mu")
#hist(run$chain[,3],main="Bias") ## if applicable
#
###########################
#### Set bycatch limit ####
###########################
#
## Parameters
#
depletion = mean(run$chain[,1]) # quantile(run$chain[,1],probs = 0.5) # in case we want a quantile
instead of mean
carry = obs[length(obs)]/depletion
IPL = 0.54
gamma = 1 ### for MSY=2%
#gamma = 2.5 ### for MSY=4%
mu = quantile(run$chain[,2],probs = 0.5)
#mu = mean(run$chain[,2]) # in case we want mean instead of a quantile
#
## Calculate the difference between depletion and the IPL
#
dif=obs[length(obs)]/carry-IPL
dif[which(dif<0)]=0
#
## Calculate bycatch limit
#
new.byc=rep(gamma*mu*obs[length(obs)]*(dif))
#
# List results
#
name.byc
depletion
carry
mu
gamma
new.byc
#
```

Appendix 3

Bycatch time series used to implement the RLA

year	hi	med	lo
1966	2004	1002	501
1967	1639	820	410
1968	1199	599	300
1969	788	394	197
1970	998	499	249
1971	791	395	198
1972	524	262	131
1973	797	398	199
1974	922	461	231
1975	1337	668	334
1976	2370	1185	592
1977	2952	1476	738
1978	4746	2373	1186
1979	3792	1896	948
1980	4126	2063	1032
1981	5175	2587	1294
1982	6246	3123	1562
1983	6147	3073	1537
1984	6352	3176	1588
1985	6005	3002	1501
1986	6824	3412	1706
1987	9960	4980	2490
1988	10023	5011	2506
1989	10152	5076	2538
1990	8336	4168	2084
1991	9749	4874	2437
1992	11062	5531	2765
1993	11356	5678	2839
1994	12363	6182	3091
1995	11887	5944	2972
1996	11060	5530	2765
1997	11370	5685	2843
1998	9905	4952	2476
1999	8512	4256	2128
2000	7360	3680	1840
2001	7471	3735	1868
2002	7632	3816	1908
2003	7462	3731	1865
2004	5239	2619	1310
2005	4435	2217	1109
2006	4094	2047	1023

2007	2616	1308	654
2008	3013	1507	753
2009	2882	1441	720
2010	3109	1554	777
2011	3505	1752	876
2012	3207	1603	802
2013	2733	1366	683
2014	2804	1402	701
2015	2552	1276	638