



Fisheries New Zealand

Tini a Tangaroa

Desktop estimation of pinniped cryptic mortality in trawls using SLEDs

New Zealand Aquatic Environment and Biodiversity Report No. 222

S. Meyer

ISSN 1179-6480 (online)

ISBN 978-0-9951271-3-5 (online)

July 2019



Requests for further copies should be directed to:

Publications Logistics Officer
Ministry for Primary Industries
PO Box 2526
WELLINGTON 6140

Email: brand@mpi.govt.nz
Telephone: 0800 00 83 33
Facsimile: 04-894 0300

This publication is also available on the Ministry for Primary Industries websites at:
<http://www.mpi.govt.nz/news-and-resources/publications>
<http://fs.fish.govt.nz> go to Document library/Research reports

© Crown Copyright – Fisheries New Zealand

TABLE OF CONTENTS

EXECUTIVE SUMMARY	1
1. INTRODUCTION	2
1.1 Scope	2
1.2 Background	2
1.3 Incentive for a user interface (cryptic mortality app)	3
1.4 Applications of the cryptic mortality app to other species interacting with fisheries	3
2. METHODS	4
2.1 Transition matrix for potential fates of sea lions that interact with trawls employing SLEDs	4
2.2 Integrating the transition matrix into a Bayesian model to estimate cryptic mortality arising from different sea lion fates	7
State predictions	7
Fitting categorical likelihood to categorical data	7
Fitting the model to non-categorical data or in the absence of data	8
2.3 Developing a graphical user interface (GUI), including user manual, to generate estimates of cryptic sea lion mortality	8
2.4 Assembling and summarizing data required for the estimation of cryptic mortality; and parameterizing prior distributions for transition parameters based on assembled data	11
Probability of MTBI (p_{MTBI})	11
Exit probability (p_{Exit})	12
Carcass retention probability ($p_{Retention}$)	13
Probability of post-exit survival ($p_{Survival}$)	13
2.5 Using the GUI to estimate cryptic mortality and to explore sensitivity of model outputs to supplied prior distributions and model variations.	15
Cryptic mortality multiplier	15
Sensitivity analysis	15
3. RESULTS	17
3.1 Exit probability (p_{Exit})	17
3.2 Cryptic mortality multiplier	19
3.3 Sensitivity analysis	20
4. DISCUSSION	22
5. MANAGEMENT IMPLICATIONS	22
6. ACKNOWLEDGMENTS	23
7. REFERENCES	23

EXECUTIVE SUMMARY

Meyer, S. (2019). Desktop estimation of New Zealand sea lion cryptic mortality in trawls using SLEDs.

New Zealand Aquatic Environment and Biodiversity Report No. 222. 25 p.

In this project, a dynamic Bayesian modelling framework was developed for the assessment of cryptic mortality of New Zealand sea lions (NZSLs) that interact with trawls using sea lion exclusion devices (SLEDs). An exclusion device provides an opening to allow sea lions to exit the trawl net, but the effect on sea lion survival and on the observability of sea lion mortality events both depend on various factors (e.g. potential loss of carcasses during net retrieval creates bias in the estimated mortality levels). The modelling framework was developed to address these factors and was informed by: data of observed NZSL captures relative to estimated total interactions with observed trawl events (to model probability of exiting the net); simulation studies (e.g. post-exit survival); and estimates based on expert knowledge (e.g. carcass retention). A base case model suggested that the total fishery-related deaths are underestimated by a factor of 1.15 (95% credible interval: 1.05–1.31) and 1.60 (95% credible interval: 1.20–2.63) for bottom trawls and mid-water trawls, respectively. Differences in the cryptic mortality multiplier were driven by modelled differences in the exit probability (the chance of sea lions exiting via the provided opening) and post-exit survival probability (survival after exiting the SLED, which is a function of time spent in the net relative to maximum breath hold time) between the two fishing methods. A sensitivity analysis to explore the effect of model variations on the estimated cryptic mortality multiplier suggested that large model alterations (e.g. of the probability of post-exit survival) are required to substantially affect the model outputs. However, most model inputs were derived from expert knowledge or simulation studies, and thus further sensitivity tests are warranted to understand if and where additional data are required. For that purpose, a graphical user interface (cryptic mortality app) has been developed, which allows efficient ad-hoc model updates to test alternate sensitivities or update input priors as new information becomes available. The results from the cryptic mortality model provide the means for adjusting estimated NZSL captures in trawl fisheries, and to integrate parameter uncertainty into those adjusted estimates.

1. INTRODUCTION

1.1 Scope

In this project, a Bayesian modelling framework was developed for the assessment of cryptic mortality of New Zealand sea lions (NZSLs) that interact with trawls. The objectives of this project were: (1) to summarize existing data required for estimating cryptic mortality of NZSLs in trawls that use a sea lion exclusion device (SLED); (2) to develop a Bayesian cryptic mortality model, including user interface, and to generate cryptic mortality estimates for sea lions by supplying parameter prior distributions informed by assembled data under Objective 1.

The project builds on hypothetical fates for NZSLs (as per Ministry for Primary Industries, 2018) that interact with fishing gear in the Auckland Islands squid fishery. In consultation with the Aquatic Environment Working Group (AEWG), existing data were evaluated for its suitability to estimate cryptic mortality (e.g. SLED field experiments and underwater video footage described in Wilkinson et al. (2003), and necropsy assessments done by Roe & Meynier (2012)). However, data required for the estimation of proposed fates are scarce, and many of the estimated parameters in this analysis rely on informed prior distributions - for example, some parameters are based on biomechanical simulations by Abraham (2011). A sensitivity analysis was carried out to assess how variations in prior distributions affect model outputs.

The specific objectives, listed in order of project completion, were:

1. Definition of a transition matrix for potential fates of sea lions that interact with trawls employing SLEDs (Objective 1);
2. Integrating the transition matrix into a Bayesian model to estimate cryptic mortality arising from different sea lion fates (Objective 2);
3. Developing a graphical user interface (GUI), including user manual, to generate estimates of cryptic sea lion mortality (Objective 2);
4. Assembling and summarizing data required for the estimation of cryptic mortality (Objective 1);
5. Parameterizing prior distributions for transition parameters based on assembled data (Objective 1);
6. Using the GUI to estimate cryptic mortality and to explore sensitivity of model outputs to supplied prior distributions and model variations (Objective 2).

1.2 Background

To mitigate captures of NZSLs in commercial trawl fisheries, SLEDs were introduced in the trawl fisheries operating in Quota Management Area SQU 6T. A SLED consists of a grid that prevents sea lions from entering the codend and instead they are directed to an opening at the top of the net. In previous years the estimation of sea lion captures, fishery related deaths, and risk relied primarily upon estimation of the annual interaction rate between NZSLs and trawls (e.g. Abraham et al. 2016). However, with increasing use of SLEDs in the SQU 6T fishery after 2001, culminating in the near-universal adoption of a standardised SLED design in the 2008 season (Ministry for Primary Industries 2019; Cleal et al. 2007), subsequently the captures model had no new information by which to estimate interactions. This was because relying upon observed captures to estimate interaction rate was confounded by SLED efficacy, and there was no empirical means of estimating how many sea lions were exiting via the SLED. Consequently, estimates from sea lion capture models became increasingly imprecise as additional years' fishing data were included (Ministry for Primary Industries, 2019). In response to this, the Spatially Explicit Fisheries Risk Assessment (SEFRA) method (Sharp 2018) was applied to sea lions in order to model sea lion interactions as a function of the spatial overlap between foraging NZSLs and trawl fishing effort, and to estimate probability of capture per interaction using fisheries observer data (Large et al. 2019).

Furthermore, there is uncertainty as to whether sea lions survive after leaving the net (hereafter referred to as post-exit survival) and whether NZSL carcasses are retained or lost via the SLED opening (hereafter

carcass non-retention). Unobservable mortality of non-target species in trawl fisheries, whether as a result of lost carcasses or due to subsequent death after leaving the net ('post-exit drowning'), is not counted among observed captures (i.e. it is 'cryptic mortality') but is an integral component of the SEFRA used in New Zealand fisheries (Sharp 2018). Consequently, a correction term to specifically adjust estimated observable NZSL captures, yielding total fishery related deaths, is required. This adjustment factor is termed the cryptic mortality multiplier.

1.3 Incentive for a user interface (cryptic mortality app)

Data are currently not available for a comprehensive assessment of all the factors (e.g. mild traumatic brain injuries, post-exit drowning) that result in cryptic mortality of NZSLs. However, quantifying how changes in those factors alter the cryptic mortality estimate can help in prioritizing the research required to fill relevant data gaps. Furthermore, as more data become available, a re-assessment of NZSL cryptic mortality might be required.

To enable scientists and stakeholders to efficiently explore variations or updates of the cryptic mortality model, a dynamic Bayesian modelling framework was implemented and made accessible via a GUI (further referred to as the cryptic mortality app). An implemented base case model (developed in consultation with the AEWG) provides a starting point to explore model variations (e.g. model structure, prior distributions) and how these variations affect the model outputs (i.e. sensitivity analysis). The cryptic mortality model is Bayesian and thus it is possible to explicitly reflect parameter uncertainty via posterior distributions. Using the cryptic mortality app, there is no need for additional coding (and knowledge thereof) and the model can be studied ad-hoc – increasing transparency and reproducibility of the results.

All results shown in this report were generated using the cryptic mortality app.

1.4 Applications of the cryptic mortality app to other species interacting with fisheries

While developed to specifically explore cryptic mortality of NZSLs in trawl fisheries using SLEDs, the cryptic mortality app could be applied to a wide range of other species and fisheries. Essentially every fishery assessment where cryptic deaths are a concern (i.e. where unintentional captures or deaths are unobservable) requires a correction term to adjust observed or estimated captures to estimate total fisheries related deaths. For example, factors affecting cryptic seabird mortality in trawl warps and longlines have been previously identified (Pierre et al., 2015). Models to investigate these processes could be easily integrated into the cryptic mortality app and adapted to other species and fisheries. Data and prior distribution updating are straightforward and therefore the app can increase the efficiency of any cryptic mortality assessment.

2. METHODS

This study specifically assessed cryptic mortality of NZSLs from the Auckland Islands (50.6218° S, 166.1196° E) that interact with trawl fisheries in Quota Management Area SQU 6T. The modelling framework and the cryptic mortality app have been presented and reviewed by the AEWG. The parameterisation of the model (i.e. state transition matrix, data acquisition, and prior distributions) was done in consultation with the AEWG. The conceptual and mathematical basis for the application of the cryptic mortality app is described in this report.

2.1 Transition matrix for potential fates of sea lions that interact with trawls employing SLEDs

NZSLs that entered the trawl net either drown inside the net or exit via the SLED opening. However, a range of events can precede and follow these two interaction outcomes. Sea lions that interact with trawl nets (i.e. being inside the net) are at risk of striking the SLED grid installed in front of the codend, which can cause mild traumatic brain injuries (MTBI) (Ponte et al. 2010). Sea lions that strike the grid might require some recovery time, which can increase their risk of drowning inside the net. Furthermore, MTBI could compromise a sea lion's post-exit survival. Even if a sea lion has not struck the grid and leaves the net, it might still run out of air and drown prior to resurfacing. Finally, dead sea lion carcasses could be lost prior to or during net hauling and landing of catch. To reflect these sea lion fates, a transition process covering the following 12 states was defined in consultation with the AEWG:

1. Interaction: a sea lion that entered the trawl net;
2. No MTBI: a fishery interaction without resulting in MTBI;
3. MTBI: a sea lion that struck the SLED grid, experienced MTBI;
4. Exit1: a sea lion without MTBI that exited the trawl net via the SLED opening;
5. Exit2: a sea lion with MTBI that exited the trawl net via the SLED opening;
6. No exit: a sea lion that has not exited the net via the SLED opening and therefore drowned during the interaction;
7. Survive1: a sea lion without MTBI exited via the SLED and survived the interaction;
8. Die1: a sea lion without MTBI exited via the SLED but died post-exit, because it reached its breath hold limit;
9. Survive2: a sea lion with MTBI exited via the SLED and survived the interaction;
10. Die2: a sea lion exited via the SLED but died due to MTBI or post-exit drowning;
11. Retained: a retained sea lion carcass that was hauled on board;
12. Lost: a sea lion carcass that dropped out of the net during net retrieval and was therefore not counted against captures;

Underwater video footage shows that NZSL also interact with the trawl net from outside the net (e.g. by removing prey from the SLED hood installed atop of the opening) (Middleton & Banks 2008). Interactions of that type are not considered in this study.

The 12 states described here are sequential and mutually dependent events. Transitions between these states were modelled via transition probabilities (Figure 1). Provided that mutually exclusive transition probabilities sum to one, a total of 6 transition probabilities were estimated (or informative prior distributions were provided when data were not available) (Figure 1 and Table 1).

The state transition process shown in Figure 1 was translated in state transition matrix \mathbf{Q} , which is a $m \times m$ -dimensional matrix (Table 2), where m denotes the number of modelled states (here, $m = 12$) and the interaction (i.e. the net entrance) reflects the first state ($m = 1$). Rows in \mathbf{Q} reflect states at the current time step t (of the modelled sequence of states) and columns reflect consecutive states at $t+1$. The state transition matrix \mathbf{Q} has two applications which are described in [Section 2.2](#).

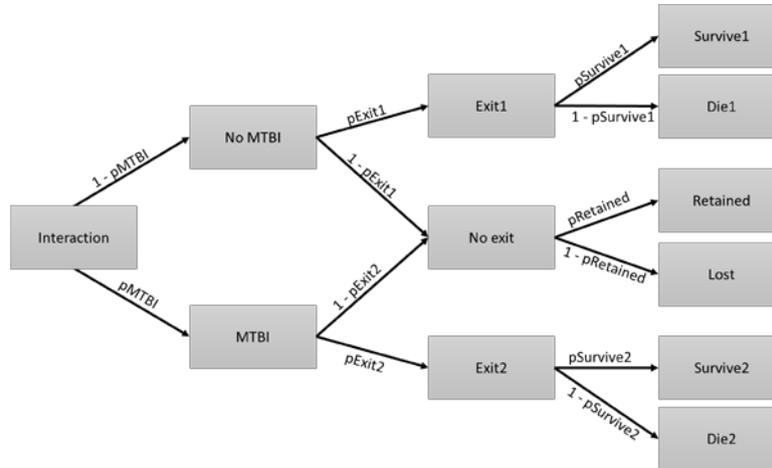


Figure 1: State transition process for NZSLs interacting with trawl nets that have SLEDs deployed, as developed under consultation with AEWG (November 2018). Boxes are categorical states and variables atop of arrows denote transition probabilities. See main text and Table 1 for details.

Table 1: Modelled transition probabilities for NZSLs states during interaction with trawls employing SLEDs.

Variable	Description
p_{MTBI}	Probability of MTBI
p_{Exit1}	Exit probability for sea lions without MTBI
p_{Exit2}	Exit probability for sea lions with MTBI
$p_{Survive1}$	Post-exit survival probability for sea lions without MTBI
$p_{Survive2}$	Post-exit survival probability for sea lions with MTBI
$p_{Retained}$	Carcass retention probability

Table 2: State-transition matrix Ω ; rows: state at time t ; columns: state at time $t+1$.

		State at time $t+1$											
State at time t	Interaction	Interaction	NoMTBI	Exit1	Survive1	Die1	NoExit	Retained	Lost	MTBI	Exit2	Survive2	Die2
	Interaction	0	$pNoMTBI$	0	0	0	0	0	0	$pMTBI$	0	0	0
	NoMTBI	0	0	$pExit1$	0	0	$pNoExit1$	0	0	0	0	0	0
	Exit1	0	0	0	$pSurvive1$	$pDie1$	0	0	0	0	0	0	0
	Survive1	0	0	0	1	0	0	0	0	0	0	0	0
	Die1	0	0	0	0	1	0	0	0	0	0	0	0
	NoExit	0	0	0	0	0	0	$pRetained$	$pLost$	0	0	0	0
	Retained	0	0	0	0	0	0	1	0	0	0	0	0
	Lost	0	0	0	0	0	0	0	1	0	0	0	0
	MTBI	0	0	0	0	0	$pNoExit2$	0	0	0	$pExit2$	0	0
	Exit2	0	0	0	0	0	0	0	0	0	0	$pSurvive2$	$pDie2$
	Survive2	0	0	0	0	0	0	0	0	0	0	1	0
	Die2	0	0	0	0	0	0	0	0	0	0	0	1

2.2 Integrating the transition matrix into a Bayesian model to estimate cryptic mortality arising from different sea lion fates

The state transition matrix has two applications: (1) generating numerical predictions of sea lions transitioning through each state for a given number of interactions; and (2) fitting a categorical likelihood to categorical data (if available for at least one pair or set of mutually dependent states).

State predictions

Using the state transition matrix $\mathbf{\Omega}$ (Table 2), the total number of interactions (this might be known, estimated, or hypothetical interactions) can be disaggregated into all modelled states by using matrix multiplication:

$$\mathbf{n}_{t+1} = \mathbf{\Omega} \times \mathbf{n}_t \quad [1]$$

where \mathbf{n}_t and \mathbf{n}_{t+1} are m -dimensional vectors containing the number of sea lions in each state at time steps t and $t+1$, and $\mathbf{\Omega}$ is the $m \times m$ -dimensional state transition matrix (see [Section 2.1](#)). At $t = 1$, \mathbf{n} has only an entry in its first element (i.e. initially, sea lions enter the trawl net). It is assumed that interactions are not known without error. That is, they are usually estimated, for example via the SEFRA framework or other methods such as described in Abraham et al. (2016). Thus, the cryptic mortality framework requires input for the mean and standard deviation of estimated interactions (assuming that estimated interactions are normally distributed).

Fitting categorical likelihood to categorical data

The model can be fitted to categorical data using the following state equations:

$$z_{i,1} = 1 \quad [2]$$

which means that every individual i starts with an interaction (state ‘Interaction’ or 1 because it occurs in row 1 and column 1 of $\mathbf{\Omega}$ (see [Section 2.1](#));

$$z_{i,t+1}/z_{i,t} \sim \text{categorical}(\boldsymbol{\pi}) \quad [3]$$

where $z_{i,t}$ and $z_{i,t+1}$ are states of individual i at time step t and $t+1$, respectively. $\boldsymbol{\pi}$ denotes a vector of non-negative probability weights taken from the $z_{i,t}$ th row of state transition matrix $\mathbf{\Omega}$. For example, if $t = 1$ (hence, $z_{i,1} = 1$) then

$$\boldsymbol{\pi} = \mathbf{\Omega}_{1,\dots} = \begin{bmatrix} 0 \\ \text{pNoMTBI} \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \text{pMTBI} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

The state equation is not fitted directly to the data, because a full sequence of the state transition process (Figure 1) is hardly ever available. Rather, parts of the state transition process are observed through specifically designed experiments (e.g. underwater camera footage to determine exit probabilities). Thus, the modelled states in equation 3 are populated into an observation process, that is:

$$y_{i,t}/z_{i,t} \sim \text{categorical}(\pi_{\text{observed}}) \quad [4]$$

where $y_{i,t}$ and $z_{i,t}$ are the observed and modelled states of individual i at time step t . π_{observed} denotes a vector of non-negative probability weights taken from the $z_{i,t}^{\text{th}}$ row of identity matrix Θ , assuming that each state is perfectly observed when obtained via specifically designed experiments.

Full records of individual (i.e. per sea lion) state transition processes are not required to fit the categorical likelihood. Rather the modelling framework allows us to fit equation 4 to only the observed part of the state transition processes (although this can be different for each individually observed sea lion) and the unobserved fraction is modelled via informative prior distributions or estimated by using alternative likelihood functions (e.g. a binary distribution). Note, that for technical reasons, within the cryptic mortality app, partial components of the state transition processes can only be fitted to data if these refer to consecutive states and if there are only two possible outcomes. However, it is possible to download the model code and modify it accordingly outside the app (see [Section 2.3](#)).

Fitting the model to non-categorical data or in the absence of data

If the model is fitted to categorical data, then transition matrix Ω provides the link between the data, the likelihood function and the prior distributions. In contrast, if no data (or no categorical data) are analysed then there is no use for Ω during the model fitting process. In this case, it is enough to define informative prior distributions (in which case they have to be informed by reflecting results from other studies or expert knowledge) or to define alternative likelihood functions (e.g. when alternative data are available). The current implementation of the base case cryptic mortality model is based on a mixture of entirely informative priors and binomially distributed data, and is explained in [Section 2.4](#).

2.3 Developing a graphical user interface (GUI), including user manual, to generate estimates of cryptic sea lion mortality

A dynamic Bayesian modelling framework (i.e. there is no fixed model structure) was developed and made accessible via a GUI, i.e. the cryptic mortality app. The cryptic mortality app is set up with the default model structure described in [Section 2.1](#) and fitted using the prior distributions and data elaborated on in [Section 2.4](#). The app generates outputs for posterior distributions of all modelled transition probabilities (including convergence diagnostics, parameter autocorrelation, etc.), disaggregates total sea lion interactions into the different modelled states, and provides an output of the cryptic mortality multiplier (see definition of the cryptic mortality multiplier in [Section 2.5](#)).

Despite the fixed base case model settings, the cryptic mortality app was developed for dynamic development and/or adjustments of all model components - i.e. state transition matrix, cryptic mortality multiplier, prior distributions and data. The app was developed using RShiny (Winston et al., 2019) and the Bayesian model, which is responsive to the app's input values, is coded in JAGS (Plummer, 2018). Along with the app, a user manual is provided. The full details of the app can be accessed through the user manual which is accessible via the app. Here the basic steps for building a cryptic mortality model are described.

Via the app, the user can provide labels for an unlimited number of states - here we modelled 12 states ([Section 2.1](#)), upon which an $m \times m$ -dimensional state transition matrix Ω is generated (Figure 2). In a next step, the user needs to parameterize Ω by entering the appropriate transition probabilities (Figure

2). Once Ω has been specified, the user can access a drop-down menu and controllers (Figure 3) to parameterize prior distributions for the transition probabilities from a given set of available distributions. Once done, the app will compile some JAGS-code, which can be downloaded, or directly executed from within the app. If executed from within the app, results are generically generated and can be downloaded for documentation and MCMC samples can be downloaded for additional post-processing. If the cryptic mortality multiplier is to be estimated, then it is necessary to specify its components from within the app.

All the analysis presented in this report was carried out using the cryptic mortality app and is based on the base case model structure and priors described in [Section 2.1](#) and [Section 2.4](#).

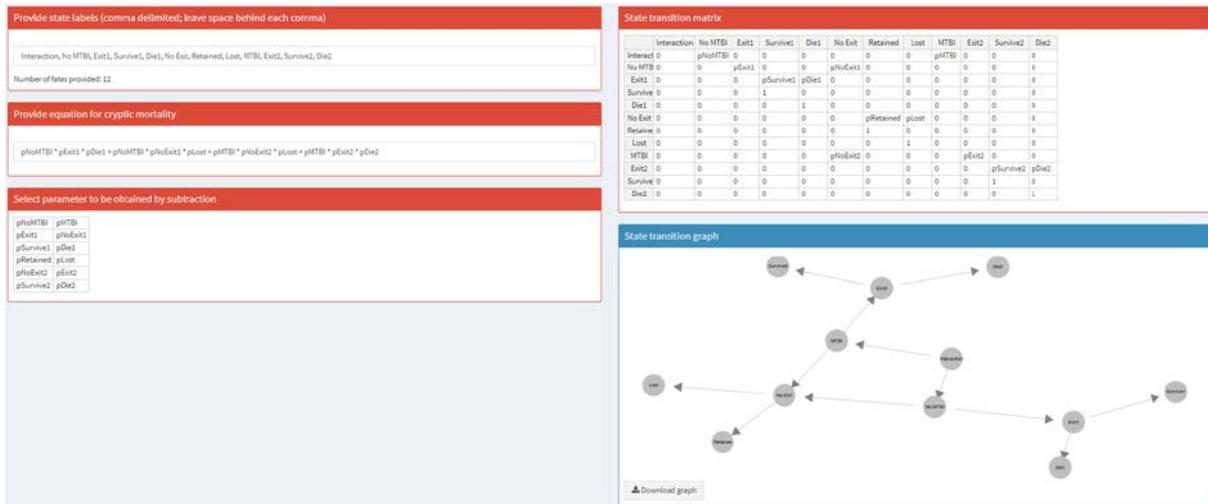


Figure 2: Front end of cryptic mortality app to set up a state-transition matrix. Here the base case model structure is shown.

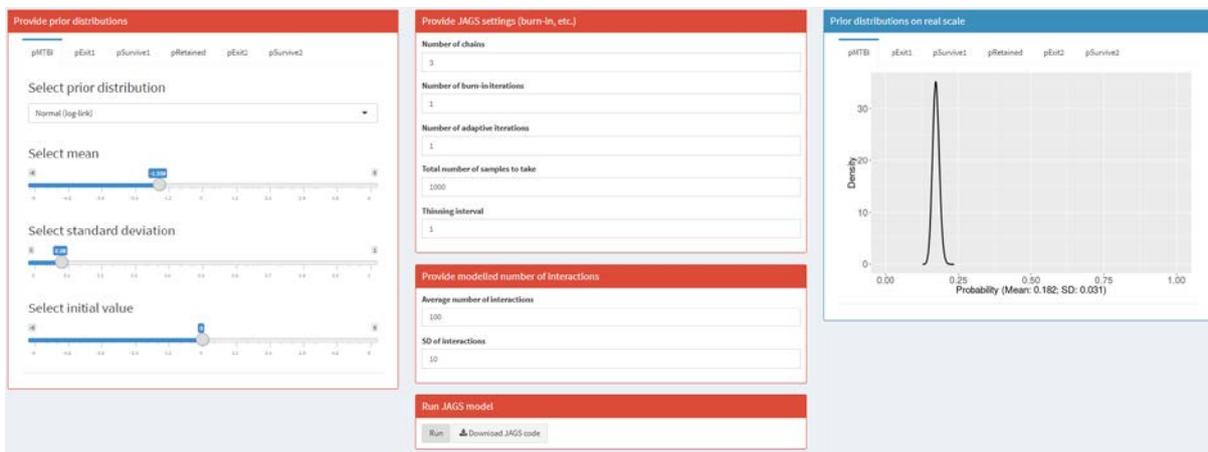


Figure 3: Front end of the cryptic mortality app to set up prior distributions and run the Bayesian model.

2.4 Assembling and summarizing data required for the estimation of cryptic mortality; and parameterizing prior distributions for transition parameters based on assembled data

Data and prior distributions for each transition probability were sought in consultation with the AEWG and were partially obtained from previous or ongoing studies. Prior distributions that the AEWG suggested and agreed on over several meetings in 2018 and 2019 are outlined below.

Note, that the base case prior distributions for p_{Exit} and $p_{Survival}$ were modelled as being identical for sea lions with and without MTBI, as opposed to the difference implied by Figure 1. The AEWG acknowledged that both the exit probability and the probability of post-exit survival are likely to be compromised by MTBI. However, currently, there is no qualitative or quantitative information to make an informed decision as to how much these rates differ between sea lions with and without MTBI. Rather than applying an arbitrary multiplier to these rates for the base case model, the decision was made by the AEWG to treat them as being identical for sea lions with and without MTBI - and to assess how this potential misspecification could affect the model output through a specific sensitivity analysis ([Section 2.5](#)).

Furthermore, the model was set up separately for bottom trawls and mid-water trawls, because some of the transition probabilities were likely to differ between the two fishing methods.

Probability of MTBI (p_{MTBI})

The probability of MTBI has been previously estimated by Abraham et al. (2011), who combined work by Ponte et al. (2010, 2011) with information obtained from underwater camera footage of Australian fur seals (*Arctocephalus pusillus doriferus*) interacting with Seal Exclusion Devices (SED) (e.g. position and speed at which seals struck the SED grid; Lyle (2011)). Abraham et al. (2011) report two estimates for the MTBI probability: (i) for a single collision and (ii) for total interactions. The MTBI probability for a single collision is conditional on a sea lion striking the grid, whereas the MTBI probability for total interactions reflects that some sea lions enter the net without such grid strike. Under the base case cryptic mortality, the state 'No MTBI' refers to sea lions without grid strike, plus those sea lions with grid strike that has not caused MTBI. In contrast, the state 'MTBI' refers to sea lions that entered the net, struck the grid, and received MTBI. The AEWG concluded that p_{MTBI} in the base case cryptic mortality model (Figure 1) corresponds to MTBI probabilities for total interactions estimated by Abraham et al. (2011).

Furthermore, Abraham et al. (2011) conducted a series of sensitivity tests to investigate how changes in model assumptions (e.g. angle of the SLED grid, sea lion head mass, etc.) alter their p_{MTBI} estimate. After consultation with the AEWG, a base case prior distribution for p_{MTBI} for the cryptic mortality model was developed, which encompasses the range of sensitivities by Abraham et al. (2011) but putting weight on the highest density of estimates and less weight on extreme values. This was realised using a log-Normal distribution centred on 0.027 (Figure 4) - the estimate for p_{MTBI} from the base case model in Abraham et al. (2011).

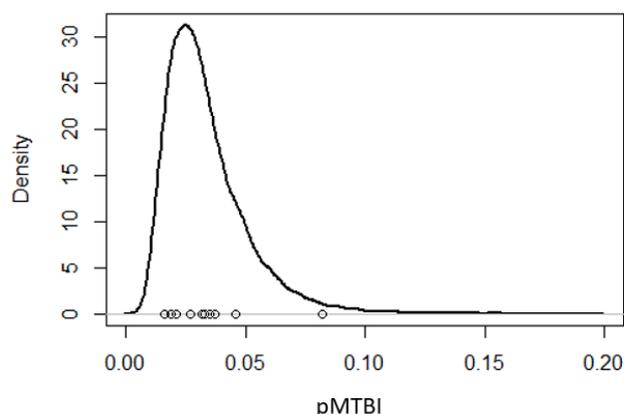


Figure 4: Log-normal prior used to model the probability of MTBI in the base case model (dots reflect estimated values for $pMTBI$ from all sensitivity tests in Abraham et al. (2011)).

Exit probability ($pExit$)

The exit probability describes the chance of sea lions exiting the trawl net via the SLED opening. Previous experiments (predominantly carried out in 2001) implied that the exit probability is high (e.g. as described in Hamilton & Baker (2015)). Since 2001, several SLED designs have been tested leading to a wide-spread use of standardized and approved SLEDs since the 2008 season (Ministry for Primary Industries 2019; Cleal et al. 2007). Based on that, the AEWG recommended to base $pExit$ on the period of standardized SLED design.

In this study, $pExit$ was derived as $1 - pNoExit$ (see Figure 1 for details on mutually dependent parameters), such that captures could be explicitly modelled as the function of the no-exit probability ($pNoExit$) and interactions. Specifically, $pNoExit$ was estimated from NZSL captures on observed tows (assuming that captures on observed tows were detected without error) relative to total interactions on observed tows. Total interactions were estimated by Large et al. (2019), which also estimated likely differences in sea lion catchability between bottom trawl and mid-water trawl fishing methods. Therefore, the cryptic mortality model was run separately for both fishing methods.

Furthermore, due to the low frequency of observed captures, the data for captures and estimated interactions were pooled for the period of standardized SLED use (2009 to 2017; Table 3 and Figure 5). Estimated interactions were assumed to be normally distributed (see Figure 5) with a mean of 27 and 31, and a standard deviation of 8 and 4, for bottom trawls and mid-water trawls, respectively (Table 3).

Table 3: Estimated interactions (from Large et al. 2019) and observed captures both on observed tows between the years 2009 and 2017.

Fishing type	Mean interactions	SD of interactions	Observed captures
Bottom trawl (BT)	27	8	10
Mid-water trawl (MW)	31	4	3

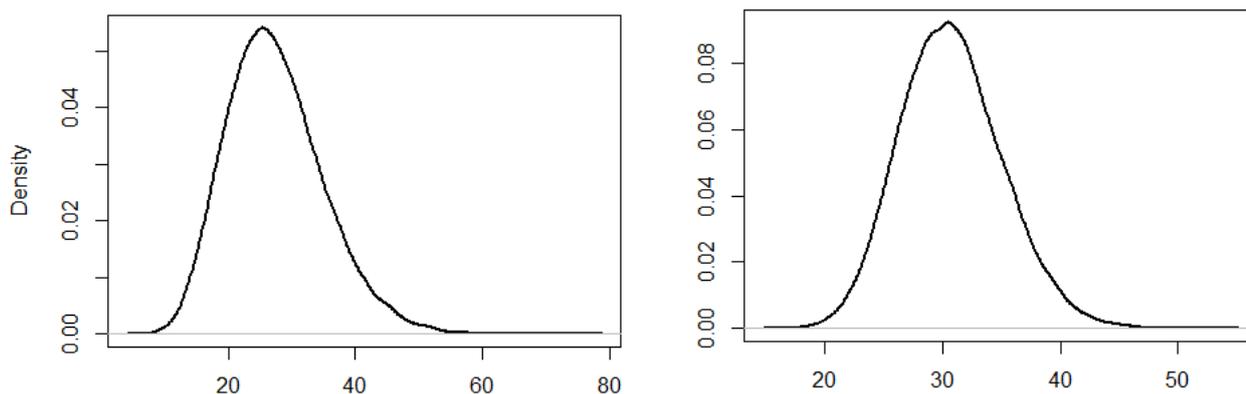


Figure 5: Posterior distributions for interactions between 2009 and 2017 for bottom trawl (left) and mid-water trawl (right). Posterior distributions were generated from MCMC samples pooled for the years 2009 to 2017 and were generated by Large et al. (2019).

To account for potential carcass loss, the model for the no-exit probability was further expanded by the retention probability. That is, sea lions are only detected as captures if they drown inside the trawl net (i.e. ‘no exit’) and if their bodies are retained in the net. Captures were modelled using a binomial distribution:

$$\text{Captures} \sim \text{dbinom}(p\text{NoExit} * p\text{Retention}, \text{Interactions}) \quad [5]$$

where $p\text{NoExit}$ was modelled using a uniform prior ranging from 0 to 1, Interactions reflect the number of trials, and $p\text{Retention}$ was modelled separately (see next Section).

Carcass retention probability ($p\text{Retention}$)

Various data sources to estimate carcass retention probability were discussed in consultation with the AEWG, such as underwater video footage showing (i) NZSLs interacting with SLEDs, (ii) arrow squid and other large fish interacting with SLEDs (Middleton (2019a)), or results of a tied-down cover-net experiment in which sea lions were retained in a second codend after exiting nets via the SLED (Wilkinson et al. 2003). However, most of the information was compromised by low frequency of sightings (NZSL interactions) or by not being an appropriate proxy species for NZSLs (arrow squid and other large fish).

The available footage, however, implied that retention of captures in trawls with deployed exclusion devices is high (Middleton 2019a and AEWG discussions). Moreover, sea lion captures are physically observed, even since the wide-spread use of SLEDs, which means that some animals are retained, i.e. a retention probability equal to zero can be ruled out. The AEWG concluded, primarily based on discussions of the hydrodynamics of fishing gear behaviour and observed negative buoyancy of drowned pinnipeds, that a uniform prior distribution from 0.90 to 0.99 provides a realistic range for $p\text{Retention}$.

Probability of post-exit survival ($p\text{Survival}$)

Previous work examined the dive duration of lactating NZSLs from the Auckland Islands in the year 1996, which was prior to the period of SLED use in SQU 6T (Crocker et al. 2001). Prior to SLED deployment, any interaction would have resulted in animals drowning. Hence, the AEWG decided that those NZSLs studied in Crocker et al. (2001) were unlikely to have extensively interacted with trawl

nets and that their observed dive duration reflects natural dive duration for lactating NZSLs (i.e. without additional fishery interaction). Dive duration ranged from 2.4 to 4.5 min (Crocker et al. 2001).

Utilizing estimates of natural dive duration for lactating NZSLs, Middleton (2019b) simulated NZSL dive durations that include fishery interactions by adding in additional dive duration due to time required to swim from net entrance to the SLED opening (based on sea lion swimming speed, distance from entrance to SLED opening and vessel approaching speed) and additional in-trawl time (based on studied Australian fur seal interactions in Australian trawl fisheries; Lyle (2011)). Mortality of simulated NZSLs occurred if the total dive duration (including time to resurface post exit) exceeded the simulated possible dive duration.

Because nets used for bottom trawling and mid-water trawling have different lengths, the hypothetical time to swim from net entrance to SLED opening differs between these two fishing methods. Thus, Middleton (2019b) generated two different estimates for post-exit survival for bottom trawling and mid-water trawling. The cryptic mortality model was run separately for both fishing methods (simultaneously with the bottom trawl and mid-water trawl-based model structure for $pExit$).

Several sensitivity tests (e.g. shape and type of distribution) were conducted by Middleton (2019b), and $pSurvival$ estimates ranged from 0.931 to 0.952, and 0.936 to 0.949 for bottom trawls and mid-water trawls, respectively. As such, uniform prior distributions for $pExit$ for bottom trawling and mid-water trawling ranging between the minimum and maximum estimates for each fishing method were implemented in the cryptic mortality model (Figure 6). One sensitivity test in Middleton (2019b) (sensitivity to trawl entry time parameterisation, leading to $pExit = 0.993$) was done for both fishing types combined and therefore not included in this analysis.

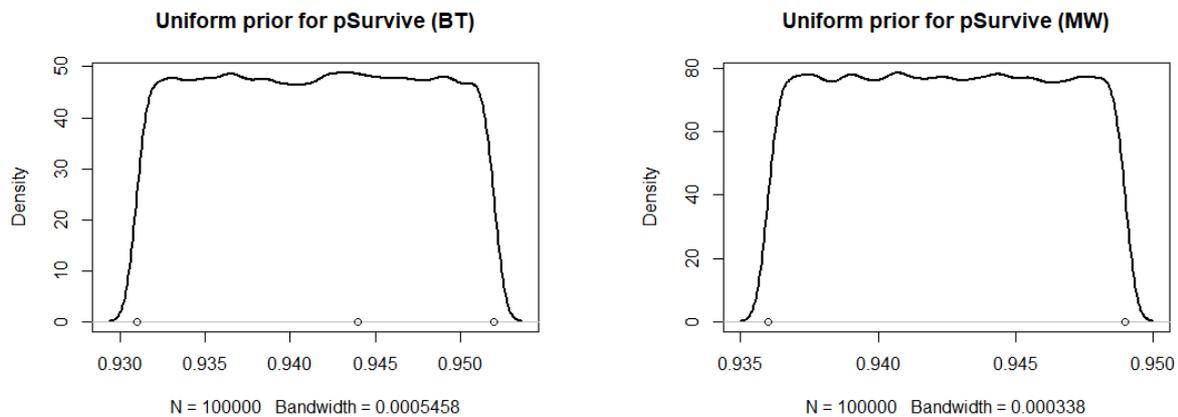


Figure 6: Uniform priors for $pSurvival$ for bottom trawls (BT; left) and mid-water trawls (MW; right) (dots reflect simulated values for $pSurvival$ in Middleton (2019b); note that three estimates are shown for MW but that two of them were identical).

2.5 Using the GUI to estimate cryptic mortality and to explore sensitivity of model outputs to supplied prior distributions and model variations.

Cryptic mortality multiplier

The prior distributions described in [Section 2.4](#), were implemented in the cryptic mortality model using the cryptic mortality app (see [Section 2.3](#)), and the associated JAGS script is provided in [APPENDIX 1](#). The cryptic mortality multiplier (κ) was calculated as:

$$\kappa = \text{Total death rate} / \text{Observable capture rate} \quad [6]$$

where the *Total death rate* is:

$$\text{Total death rate} = \text{Observable capture rate} + \text{Cryptic mortality rate} \quad [7].$$

For the base case model, the *Observable capture rate* and *Cryptic mortality rate* are directly obtained from the cryptic mortality model as:

$$\text{Observable capture rate} = p_{\text{NoMTBI}} * p_{\text{NoExit1}} * p_{\text{Retained}} + p_{\text{MTBI}} * p_{\text{NoExit2}} * p_{\text{Retained}} \quad [8]$$

and

$$\text{Cryptic mortality rate} = p_{\text{NoMTBI}} * p_{\text{Exit1}} * p_{\text{Die1}} + p_{\text{NoMTBI}} * p_{\text{NoExit1}} * p_{\text{Lost}} + p_{\text{MTBI}} * p_{\text{NoExit2}} * p_{\text{Lost}} + p_{\text{MTBI}} * p_{\text{Exit2}} * p_{\text{Die2}} \quad [9].$$

Note that *Observable capture rate* refers to captures that would be recorded if all tows were observed.

Sensitivity analysis

Sensitivity tests were carried out based on decisions made by the Squid Operational Technical Advisory Group (June 2019). These sensitivity tests were done to explore the potential bias in the cryptic mortality multiplier by assuming an identical exit probability and post-exit survival for sea lions with and without MTBI. Additionally, sensitivities were explored to test how changes in the anticipated retention probabilities would affect the cryptic mortality multiplier. All sensitivity tests were carried out independently from each other (Table 4).

Table 4: Summary of sensitivity tests applied to base case cryptic mortality model.

Sensitivity test	Description	Model implementation
1	All animals with MTBI do not exit	$pNoExit2 = 1.000$
2	All animals with MTBI that do exit, die	$pSurvive2 = 0.000$
3	Retention probability has the same shape and width as for the base case model but is left shifted to centre on 0.8 (i.e. on average 20% of carcasses are lost)	$pRetention \sim Uniform(0.755, 0.845)$ ¹
4	Retention probability has the same shape and width as for the base case model but is left shifted to centre on 0.2 (i.e. on average 80% of carcasses are lost)	$pRetention \sim Uniform(0.155, 0.245)$ ¹
5	Doubling the mean of '1-pSurv' and maintain width of distribution (i.e. twice as many animals drown after exiting the net: 12% rather than 6%).	$pSurvival_{doubled\ mortality, BT} \sim Uniform(0.862, 0.904)$ ² $pSurvival_{doubled\ mortality, MW} \sim Uniform(0.872, 0.898)$ ²

¹ $a_{new} = a - \{[0.5*(a+b)] - \mu_{new}\}$; $b_{new} = b - \{[0.5*(a+b)] - \mu_{new}\}$; where a and b are the lower and upper bound of the original uniform distribution; a_{new} and b_{new} are the lower and upper bound of the new uniform distribution, μ_{new} is the proposed mean of the new uniform distribution.

² $pDie_{doubled\ mortality} = (1 - Survival) * 2$; $pSurvival_{doubled\ mortality} = 1 - pDie_{doubled\ mortality}$

3. RESULTS

All models were implemented and executed using the cryptic mortality app developed in this study. Each model (i.e. bottom trawl versus mid-water trawl, and sensitivity tests) was run with a burn-in phase of 140 000 iterations and followed by 60 000 iterations with samples taken every 5th iteration. For estimated parameters (here, $pExit$), convergence was assessed using the potential scale reduction factor (Brooks & Gelman 1998).

3.1 Exit probability ($pExit$)

Total interactions (on observed hauls only) were obtained from the outputs of Large et al. (2019); models were then fit to observed capture rates to estimate exit probability separately for bottom trawling and mid-water trawling. The resulting posteriors highlighted differences in the estimated exit probability between these two fishing methods; there was also substantially greater uncertainty for the cryptic mortality multiplier for bottom trawling than for mid-water trawling (Figure 7).

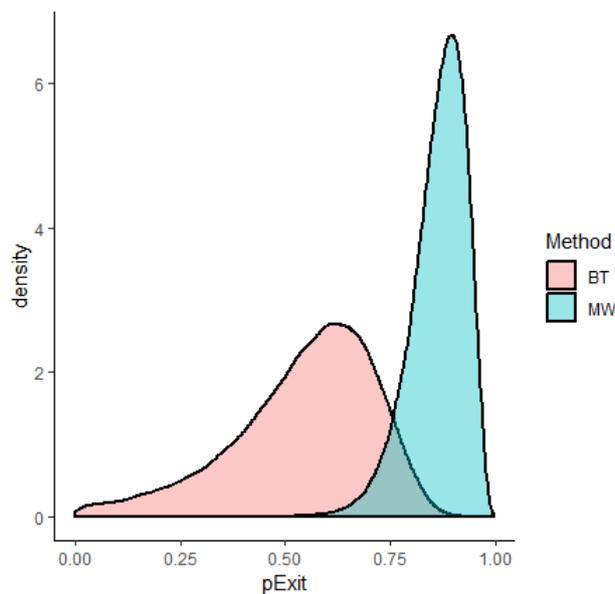


Figure 7: Posterior distributions of the exit probability for NZSLs interacting with bottom trawls (BT) and mid-water trawls (MW).

For bottom trawling, on average 57% (i.e. $pExit = 0.57$) of NZSLs that entered the trawl net exited via the SLED opening (Table 5). However, the 95% credible interval ranged between 0.14 and 0.80, implying that not enough data exist to inform the estimation of $pExit$ for sea lions interacting with bottom trawling. For mid-water trawling, an average $pExit$ of 0.88 (or 88% of NZSLs exiting via the SLED opening) was estimated, and the 95% credible interval ranged from 0.71 to 0.96 (Table 5).

Table 5: Summary statistics of the exit probability (*pExit*) for NZSLs interacting with bottom trawls and mid-water trawls.

Fishing method	Mean (Median)	95% credible interval
Bottom trawl (BT)	0.57 (0.54)	0.14–0.80
Mid-water trawl (MW)	0.88 (0.87)	0.71–0.96

3.2 Cryptic mortality multiplier

Differences in both the exit probability and post-exit survival (see [Section 2.4](#)) between bottom trawling and mid-water trawling were also reflected in the estimated cryptic mortality multiplier (Figure 8). For bottom trawling, the mean cryptic mortality multiplier was 1.15 with a 95% credible interval of 1.05 to 1.31 (Table 6). In other words, the total deaths were, on average, 1.15 times higher than the observed captures (i.e. those captures that were observed being landed on board the fishing vessel). For mid-water trawling, a higher cryptic mortality multiplier was estimated. Here, the actual total deaths were, on average, 1.60 (95% credible interval: 1.20–2.63) higher than the observed (or estimated) captures (Table 6).

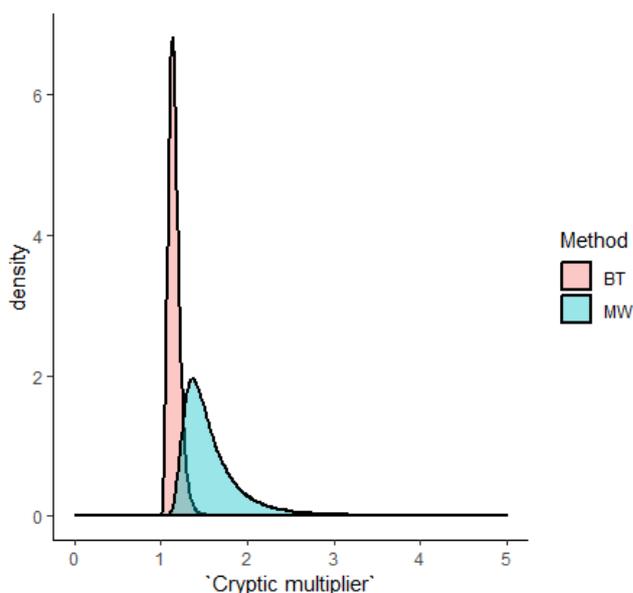


Figure 8: Posterior distributions of the cryptic mortality multiplier for NZSLs interacting with bottom trawls (BT) and mid-water trawls (MW).

Table 6: Summary statistics of the cryptic mortality multiplier for NZSLs interacting with bottom trawls (BT) and mid-water trawls (MW).

Fishing method	Mean (Median)	95% credible interval
Bottom trawl (BT)	1.15 (1.14)	1.05–1.31
Mid-water trawl (MW)	1.60 (1.49)	1.20–2.63

3.3 Sensitivity analysis

A total of 5 model variations were assessed, for both bottom trawling and mid-water trawling. Each sensitivity test showed that the model is working as anticipated. For example, for bottom trawling, the model was insensitive to a re-parameterisation of the base case model such that all sea lions with MTBI drown inside the net (Sensitivity test 1 in Table 7). Here, the cryptic mortality multiplier changed from 1.15 (95% credible interval: 1.05–1.31) to 1.14 (95% credible interval: 1.05–1.28) (Table 7). This was expected, because the modelled MTBI probability was small (on average 0.027), hence a change of $pExit2$ (i.e. exit probability for sea lions with MTBI) affects only a small fraction of all sea lion interactions. For the same reason, only small changes of the cryptic mortality multiplier were observed when assuming that all animals with MTBI would die post exit (Sensitivity test 2 in Table 7).

Shifting the retention probability from a uniform distribution centred on 0.945 (base case model) to a uniform distribution centred on 0.8 caused small changes of the cryptic mortality multiplier for both fishing methods (Sensitivity test 3 in Table 7). As per base case model, most sea lions will exit the net, and thus not many of the modelled animals will be affected by a change in $pRetention$. Only after a large shift of the retention probability (to a uniform distribution centred on 0.2; Sensitivity test 4 in Table 7) was a large (4-fold) increase in the cryptic mortality multiplier observed.

Doubling the post-exit mortality (Sensitivity test 5 in Table 7), irrespective of whether sea lions were affected by MTBI or not, also led to a small increase in the cryptic multiplier. This effect was stronger for mid-water trawling – reflecting the fact that more animals seem to exit via SLEDs in mid-water trawl gear than in bottom trawl gear (i.e. more sea lions can transition to the states ‘Survive1’ and ‘Survive2’).

Table 7: Results of sensitivity analysis for bottom trawl (BT) and mid-water trawl (MW). Shown are the mean cryptic mortality multiplier (median in brackets) and 95% credible interval (CrI).

Sensitivity test	Description	Cryptic multiplier (BT)	Cryptic multiplier (MW)
0	Base case	1.15 (1.14); 95% CrI: 1.05–1.31	1.60 (1.49); 95% CrI: 1.20–2.63
1	All animals with MTBI do not exit	1.14 (1.14); 95% CrI: 1.05–1.28	1.44 (1.39); 95% CrI: 1.18–1.96
2	All animals with MTBI that do exit, die	1.20 (1.19); 95% CrI: 1.06–1.46	1.89 (1.72); 95% CrI: 1.28–3.56
3	Retention probability has the same shape and width as for the base case model but is left shifted to centre on 0.8	1.29 (1.33); 95% CrI: 1.22–1.50	1.78 (1.67); 95% CrI: 1.38–2.83
4	Retention probability has the same shape and width as for the base case model but is left shifted to centre on 0.2	4.78 (4.63); 95% CrI: 4.13–6.20	5.48 (5.41); 95% CrI: 4.30–7.04

4. DISCUSSION

A dynamic Bayesian modelling framework for assessing NZSL cryptic mortality in trawls, with SLEDs deployed, was developed in this study. The Bayesian model is accessible through a GUI (cryptic mortality app) and no or little coding experience is required for model implementation. The interface was deployed with a base case cryptic mortality model that was developed in consultation with the AEWG.

The base case cryptic mortality model suggested that total fishery-related deaths (i.e. including observed and unobserved captures, carcasses that are lost before or during the haul, and sea lions that die after leaving the net) are underestimated by a factor of 1.15 (95% credible interval: 1.05–1.31) and 1.60 (95% credible interval: 1.20–2.63) for bottom trawls and mid-water trawls, respectively. Differences in the cryptic mortality multiplier were driven by modelled differences in the exit probability and post-exit survival probability between the two fishing methods.

The sensitivity analysis showed plausible changes of the cryptic mortality multiplier in response to altered transition probabilities. Nonetheless, only large alterations of transition probabilities resulted in substantial changes of the cryptic mortality multiplier. It is worth noting that the exit probability (or no-exit probability) was the only explicitly estimated parameter (i.e. being informed by observed captures data). Prior distributions for all other parameters were based on expert knowledge or output from simulation studies. Updating those prior distributions with actual data could potentially produce different results than those generated under this study.

Some additional aspects could be further investigated via the cryptic mortality model. NZSLs that interacted with fishing gear could enter the same or a different trawl net again (either on the same foraging trip or on consecutive trips), and such behaviour could potentially affect any of the modelled transition probabilities. For example, sea lions that re-enter the net might be more likely to exit the net due to previous experience. Despite not being within the scope of this study, indirect effects on NZSL foraging behaviour could be investigated, such as the effect of exceeding the aerobic dive limit (Chilvers et al. 2006; Chilvers & Wilkinson 2009) during fishery interaction on demographic parameters.

5. MANAGEMENT IMPLICATIONS

The results from the base case cryptic mortality model provide the means for adjusting current estimates of NZSL fisheries related deaths in trawl fisheries using SLEDs in areas adjacent to the Auckland Islands. Crucially, the modelling framework allows the integration of uncertainty through to the estimate of the cryptic mortality multiplier. Therefore, parameter uncertainty could potentially be reflected in adjusted estimates of NZSL deaths.

The sensitivity analysis showed that changes in the cryptic mortality multiplier are small when transition probabilities were altered, in what was considered a realistic range. However, big changes in transition probabilities for carcass non-retention and post-escape drowning resulted in much higher values for the cryptic mortality multiplier, highlighting that data gaps for the cryptic mortality model can have significant implications for the estimation of fishery-related mortality of NZSL. Further, more specific, sensitivity tests could be carried out to understand where data gaps need to be filled.

6. ACKNOWLEDGMENTS

This work was contracted by the Ministry for Primary Industries – Fisheries New Zealand (project code: PMM2018-09). It was revised by the Fisheries New Zealand Aquatic Environment Working Group over several meetings in the years 2018 and 2019. I thank Ben Sharp and Marianne Vignaux for helpful comments on the draft of this report.

7. REFERENCES

- Abraham, E.R. (2011). Probability of mild traumatic brain injury for sea lions interacting with SLEDs. In: Final Research Report for Ministry of Fisheries project SRP2011-03 (Unpublished report held by Fisheries New Zealand, Wellington). 21 pages.
- Abraham, E.R.; Richard, Y.; Berkenbusch, K.; Thompson, F. (2016). Summary of the capture of seabirds, marine mammals, and turtles in New Zealand commercial fisheries, 2002–03 to 2012–13. *New Zealand Aquatic Environment and Biodiversity Report No. 169*. 205 pages.
- Brooks, S.P.; Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of computational and graphical statistics*, 7(4), 434–455.
- Chilvers, B.L.; Wilkinson, I.S.; Duignan, P.J.; Gemmell, N.J. (2006). Diving to extremes: are New Zealand sea lions (*Phocarctos hookeri*) pushing their limits in marginal habitat? *Journal of Zoology* 269 (2): 233–240. doi:10.1111/j.1469-7998.2006.00059.x.
- Chilvers, B.L.; Wilkinson, I.S. (2009). Diverse foraging strategies in lactating New Zealand sea lions. *Marine Ecology Progress Series*, 378, 299–308.
- Cleal, J.; Clement, G.; Wells, R. (2007). Squid Trawl Fleet Sea Lion Escape Device Audit. A Report Commissioned by Department of Conservation. Unpublished report held by Fisheries New Zealand.
- Crocker, D.E.; Gales, N.J.; Costa, D.P. (2001). Swimming speed and foraging strategies of New Zealand sea lions (*Phocarctos hookeri*). *Journal of Zoology* 254 (2): 267–277.
- Hamilton, S.; Baker, G.B. (2015). Review of research and assessments on the efficacy of sea lion exclusion devices in reducing the incidental mortality of New Zealand sea lions *Phocarctos hookeri* in the Auckland Islands squid trawl fishery. *Fisheries Research*, 161, 200–206.
- Large, K.; Robertson, J., Spatial fisheries risk assessment of New Zealand sea lions at the Auckland Islands (2019). *New Zealand Aquatic Environment and Biodiversity Report No. 224*.
- Lyle, J. (2011). Fur seal interactions with SED excluder device. Final Research Report for project SRP2010-03 (Unpublished report held by Fisheries New Zealand, Wellington).
- Middleton, A.J.; Banks, D.A. (2008). Analysis of underwater video footage of SLEDs from the 2008 squid fishery. Final report for Deepwater Group Ltd.
- Middleton, D.A.J. (2019a) Information on SLED retention from SLED video studies. Unpublished report to Fisheries New Zealand.
- Middleton, D.A.J. (2019b). Simulating sea lion dives to assess the probability of post-escape drowning for sea lions exiting SLEDs. *New Zealand Aquatic Environment and Biodiversity Report* 225. 31 p
- Ministry for Primary Industries (2018). RFP: Desktop estimation of pinniped cryptic mortality in trawls using SLEDs 405829 PMM2018-09.
- Ministry for Primary Industries (2019). Aquatic Environment and Biodiversity Annual Review 2018. Chapter 4. Compiled by the Fisheries Science Team, Ministry for Primary Industries, Wellington New Zealand. 704 p.
- Pierre, J.P.; Richard, Y.; Abraham, E.R. (2015). Assessment of cryptic seabird mortality due to trawl warps and longlines, 51 p. Final Report prepared for the Department of Conservation: Conservation Services Programme project INT2013-05.
- Plummer, M. (2018). rjags: Bayesian Graphical Models using MCMC. R package version 4-8. <https://CRAN.R-project.org/package=rjags>

- Ponte, G.; van den Berg, A.; Anderson, R.W.G. (2010) Impact characteristics of the New Zealand Fisheries sea lion exclusion device stainless steel grid. Report for Ministry of Fisheries. Centre for Automotive Research, The University of Adelaide, Australia.
- Ponte, G.; van den Berg, A.; Anderson, R.W.G. (2011). Further analysis of the impact characteristics of the New Zealand Fisheries sea lion exclusion device stainless steel grid. Report for Ministry of Fisheries. Centre for Automotive Research, The University of Adelaide, Australia
- Roe, W.D.; Meynier, L. (2012). Review of necropsy records for bycaught New Zealand sea lions (*Phocarcos hookeri*), 2000–2008. *New Zealand Aquatic Environment and Biodiversity Report No. 98*, 43 p.
- Sharp, B.R. (2018). Spatially-explicit fisheries risk assessment (SEFRA): a framework for quantifying and managing incidental commercial fisheries impacts on non-target species. In: Aquatic Environment and Biodiversity Annual Review 2017. Ministry for Primary Industries. pp. 20–56. URL <https://www.mpi.govt.nz/dmsdocument/27471-aquatic-environment-and-biodiversity-annual-review-aebar-2017-a-summary-of-environmental-interactions-between-the-seafood-sector-and-the-aquatic-environment>
- Wilkinson, I.; Burgess, J.; Cawthorn, M. (2003). New Zealand sea lions and squid—managing fisheries impacts on a threatened marine mammal. In: Gales, N., Hindell, M., Kirkwood, R. (Eds.), *Marine mammals: Fisheries, tourism and management issues*. CSIRO Publishing, Melbourne, pp. 192–207.
- Winston, C.; Cheng, J.; Allaire, J.J.; Xie, Y.; McPherson, J. (2019). shiny: Web Application Framework for R. R package version 1.3.2. <https://CRAN.R-project.org/package=shiny>

APPENDIX 1: JAGS CODE TO FIT CRYPTIC MORTALITY MODEL (BOTTOM TRAWL)

```
model{  
  
  ## Priors and likelihoods  
  # Probability of mild traumatic brain injury  
  pMTBI ~ dlnorm(-3.510874, 1/pow(0.4717304,2)); # Based on simulations done by Abraham et al. (2011)  
  
  # No-exit probability  
  Captures ~ dbinom(pNoExit * pRetained, Interactions); # provide Captures as data  
  
  pNoExit ~ dunif(0, 1);  
  
  Interactions <- round(I_distr);  
  I_distr ~ dnorm(27.45425, tau); # Based on estimated interactions on observed trawls (Large et al. 2019)  
  sigma <- 7.617811; # Based on estimated interactions on observed trawls (Large et al. 2019)  
  tau <- pow(sigma, -2);  
  sigma2 <- pow(sigma, 2);  
  
  # Post-exit survival probability  
  pSurvive ~ dunif(0.931, 0.952); # Based on simulations done by Middleton (2019)  
  
  # Retention probability  
  pRetained ~ dunif(0.9, 0.99); # Based on decision made by AEWG (June 2019)  
  
  ## Derived parameter  
  # Transition probabilities  
  pNoExit1 <- pNoExit;  
  pNoExit2 <- pNoExit;  
  
  pSurvive1 <- pSurvive;  
  pSurvive2 <- pSurvive;  
  
  pNoMTBI = 1 - pMTBI;  
  pExit1 = 1 - pNoExit1;  
  pDie1 = 1 - pSurvive1;  
  pLost = 1 - pRetained;  
  pExit2 = 1 - pNoExit2;  
  pDie2 = 1 - pSurvive2;  
  
  # Cryptic mortality multiplier  
  cryptic_mortality_rate <- pNoMTBI * pExit1 * pDie1 + pNoMTBI * pNoExit1 * pLost + pMTBI * pNoExit2 * pLost + pMTBI *  
  pExit2 * pDie2;  
  
  observed_mortality_rate <- pNoMTBI * pNoExit1 * pRetained + pMTBI * pNoExit2 * pRetained;  
  
  cryptic_multiplier <- (cryptic_mortality_rate + observed_mortality_rate) / observed_mortality_rate;  
}
```