Defence Research and Development Canada
Recherche et développement pour la défense Canada

DRDC | RDDC
technologysciencetechnologie

A multidisciplinary approach for mitigating the risk of harm to marine mammals from sound exposure

Andrew C. Day
DRDC – Atlantic Research Centre

Defence Research and Development Canada
Scientific Report
DRDC-RDDC-2022-R032
February 2022

Canada

IMPORTANT INFORMATIVE STATEMENTS

This document was reviewed for Controlled Goods by Defence Research and Development Canada (DRDC) using the Schedule to the *Defence Production Act*.

Disclaimer: This publication was prepared by Defence Research and Development Canada, an agency of the Department of National Defence. The information contained in this publication has been derived and determined through best practice and adherence to the highest standards of responsible conduct of scientific research. This information is intended for the use of the Department of National Defence, the Canadian Armed Forces ("Canada") and Public Safety partners and, as permitted, may be shared with academia, industry, Canada's allies, and the public ("Third Parties"). Any use by, or any reliance on or decisions made based on this publication by Third Parties, are done at their own risk and responsibility. Canada does not assume any liability for any damages or losses which may arise from any use of, or reliance on, the publication.

Endorsement statement: This publication has been peer-reviewed and published by the Editorial Office of Defence Research and Development Canada, an agency of the Department of National Defence of Canada. Inquiries can be sent to: Publications.DRDC-RDDC@drdc-rddc.gc.ca.

Abstract

This Scientific Report reviews the models that make up existing decision support tools for mitigating the risk of sonar exposure to marine mammals. The models include: a density model to simulate the location of marine mammals, an acoustic model to determine sound propagation, an exposure model to determine the total sound exposure and impact to a simulated mammal, and behaviour models that allow the simulated mammal to move through the sound field. Although the challenges are considerable, understanding the workflow of the various models and the importance of the data is key. Joining the models into a system or workbench, does progress the work towards a mitigation tool. However, incorporating defined risk assessment measures that address mammal-specific requirements is a critical component.

Using aspects of financial risk management, examples of risk measures that may be applicable to quantifying risk of harm to marine mammals due to sound exposure are described. In addition, the complexity of risk and of combining these models into a single tool for marine mammal risk mitigation is highlighted. A deficiency in data and issues associated with real-time data assimilation into many of the models are also indicated.

Significance for defence and security

A decision support tool would give the CAF the ability to plan sonar exercise locations that minimize the risk to marine mammals due to sound exposure. Expanding the employed mitigation measures by leveraging existing data, application of risk modelling would provide a risk forecasting ability. Thus, allowing the CAF to better plan and carry out exercises while reducing risk to mammals and alleviating some of the mitigation burdens on operators in the field. Effectively this means an ability to conduct an exercise while satisfying the CAF's requirement to uphold the spirit of marine mammal protections, like the Species at Risk Act, while potentially improving force generation.

Résumé

Ce rapport passe en revue les modèles qui composent les outils d'aide à la décision existants pour atténuer le risque d'exposition des sonars aux mammifères marins. Les modèles comprennent : un modèle de densité pour simuler l'emplacement des mammifères marins, un modèle acoustique pour déterminer la propagation du son, un modèle d'exposition pour déterminer l'exposition sonore totale et l'impact sur un mammifère simulé, et des modèles de comportement qui permettent au mammifère simulé de se déplacer à travers le champ sonore. Bien que les défis soient considérables, comprendre le workflow des différents modèles et l'importance des données est essentiel. L'intégration des modèles dans un système ou un plan de travail fait progresser le travail vers un outil d'atténuation. Cependant, l'incorporation de mesures d'évaluation des risques définies qui répondent aux exigences spécifiques aux mammifères est un élément essentiel.

À l'aide d'aspects de la gestion des risques financiers, des exemples de mesures de risque qui peuvent être applicables à la quantification du risque de dommages aux mammifères marins en raison d'une exposition sonore sont décrits. De plus, la complexité du risque et de la combinaison de ces modèles en un seul outil d'atténuation des risques pour les mammifères marins est soulignée. Un manque de données et des problèmes associés à l'assimilation de données en temps réel dans de nombreux modèles sont également indiqués.

Importance pour la défense et la sécurité

Un outil d'aide à la décision donnerait aux FAC la capacité de planifier des emplacements d'exercice de sonar qui minimisent le risque pour les mammifères marins en raison de l'exposition au bruit. En élargissant les mesures d'atténuation employées en tirant parti des données existantes, l'application de la modélisation des risques fournirait une capacité de prévision des risques. Ainsi, permettant aux FAC de mieux planifier et effectuer des exercices tout en réduisant les risques pour les mammifères et en allégeant certains des fardeaux d'atténuation pour les opérateurs sur le terrain. En fait, cela signifie une capacité de mener un exercice tout en satisfaisant l'exigence des FAC de respecter l'esprit des protections des mammifères marins, comme la Loi sur les espèces en péril, tout en améliorant potentiellement la génération de force.

Table of contents

List of figures

List of tables

Acknowledgements

I would like to thank Anthony Isenor for constructive criticism during the making of this Report. In addition, I am grateful for the reference contributions and helpful discussions provided by Craig Reesor.

1 Introduction

The Species at Risk Act (SARA) and the Fisheries Act provide protections to marine life against disturbances, killing, harm, harassment, and capture. Although some actions that result in the killing or capture of marine wild life would be considered clear, actions that produce disturbances, harm, or harassment are more nebulous. Due to Canada's enforcement of the Oceans Protection Plan, SARA, and the Fisheries Act the Canadian Armed Forces (CAF) have a duty to mitigate risks to marine wildlife while still meeting its own defence mandate. For the CAF this dilemma is most prominent during operations, where there is a risk of harming or harassing marine mammals with sound introduced into the water column from sonar systems [1]. There are currently operational mitigation strategies to minimize this risk, discussed in Subsection 1.1, but these operational measures are imperfect.

The latest generation of the Royal Canadian Airforce (RCAF) acoustic systems introduce low-frequency active sound into the water column. These systems, collectively referred to as low-frequency active sonar (LFAS), have been modelled from a marine mammal perspective, with results indicating that the increased sound energy at lower frequencies could not be mitigated [2]. This is due to the acoustic waves having longer propagation ranges at an increased source level. As a result, the Department of Fisheries and Oceans (DFO) was notified in November 2020 of a section 83 exception to SARA to conduct sonar exercises for the purposes of national security. Although the exception allows the CAF to continue exercises, the CAF is continuing efforts to uphold the spirit of SARA through ongoing research into marine mammal mitigation measures.

Risk of harm to marine mammals due to sonar can be categorized by short and long term impacts. The immediate, or short term, impacts can include death, injury, stranding, behavioural changes, impaired communications ("masking"), and temporary/permanent hearing damage known as temporary/permanent threshold shifts (TTS/PTS), respectively [3]. However, these short term impacts in combination with frequent use of sonar in an area could have long term impacts on the marine mammal population. For example, changes in feeding habits due to repeated sonar use in traditional feeding grounds. It is the risk of harm in both time scales that mitigation measures hope to reduce.

In August 2020, the RCAF issued a directed client support (DCS) task to explore the development of a decision support tool for marine mammal risk mitigation.[1] Supplementing the RCAF DCS task are Maritime Forces Pacific (MARPAC) and Atlantic (MARLANT) Safety and Environment (SE) DCS tasks issued in August and September 2020, respectively. The MARPAC and MARLANT DCS tasks incorporate automated detections and autonomous systems as additional information sources for marine mammal mitigation. These additional sources would then feed into the support tool and provide quasi-time risk assessment updates for planned sonar exercises. This would contribute to efforts by the RCAF and RCN to revamp marine mammal mitigation.

[1] Hereafter, marine mammal risk mitigation refers to reducing the risk of harm to marine mammals from sonar. Similarly, risk of sound exposure implies risk of harm due to sound exposure.

The armed forces from a number of other countries, including the United States (US), the Netherlands (NL), Norway, and the United Kingdom (UK), are also actively researching decision support tools to reduce the probability of inflicting harm on marine mammal species. The CAF, however, does not currently use such a tool. It is the purpose of this document to present how these tools operate and can be used to further mitigate the risk to marine mammals and streamline mitigation procedures of the CAF.

This Scientific Report provides an overview of key parameters and metrics used in probabilistic models of marine mammal mitigation, data sources used in model calibration, and a discussion on how to quantify the different sources of risk posed to marine mammals that are captured in these models. Additionally, this report serves as a scoping study that addresses the DCS task's stated need for a review of existing mitigation tools as well as key metrics and parameters used within them to quantify risk to marine mammals due to sound exposure.

1.1 Current operational mitigation

The CAF currently employs a series of operational measures to mitigate the risk of harming marine mammals during sonar activities [4]. This starts with crew awareness training for detecting and classifying marine mammals while at sea.

The active mitigation strategy begins with a visual search of the mitigation avoidance zone (MAZ) from a helicopter followed by a two minute ramp up of the sound source level of the deployed sensors until it reaches normal operating level. The theory being that the increasing sound level will cause nearby marine mammals to leave the operational zone [5]. When practical, passive acoustic monitoring of the operation area for marine mammals is also employed during the initial observation period, ramp up, and transmission phases.

The MAZ is defined by a circle centered at the sound source with a radius based on the technical specifications of the sound source and how the sound exposure relates to a probability of a response on the mammal (termed a dose-response curve). Consecutive dips/buoys are also separated by 2×MAZ radius to prevent overlapping zones. The MAZ is sensor-specific and not dependent on the environment the sensor is deployed. Table 1 lists several example MAZ radiuses and their corresponding sensors.

Table 1: *Example MAZ by sensor.*

Sensor	MAZ radius
DS-100 HELRAS dipping sonar	3000 m
AN/SSQ-565 multistatic source sonobuoys	700 m
AN/SSQ-62 DICASS sonobuoys	300 m

During the transmission phase the MAZ is observed by operators in the helicopter and additional sensors (electro-optical and infrared sensors, and radar) when practical. Shut down procedures are initiated if a marine mammal is observed entering the MAZ. Active transmission is suspended until the marine mammal has, or believed to have, left the MAZ.

1.2 Structure

Section 2 describes the individual model components that make up existing decision support tools for marine mammal mitigation. Table 2 summarizes the existing tools and cites the models used in these tools from the literature.

Section 3 provides a quick background in risk measures from the field of financial mathematics. These risk measures can be applied to any distributions, model parameters, or variables resulting from the models in Section 2 in order to provide a risk assessment for a decision making process.

Section 4 details the data requirements for the models and possible complicating factors that arise from the different types of data that are critical for the success of the tool.

Section 5 then provides final remarks on the work flow of the models seen in Section 2 and how they feed into one another. The goal being to set up a workbench that can be used to simulate sonar exercises and explore ways to quantify the impacts on marine mammals; the model outputs are then fed into a risk assessment layer. A final decision support tool can then be built from the lessons learned with this workbench.

2 Decision support tools

Decision support tools are comprised of three main components: a mammal density model, an acoustic model, and a sound exposure model. A convenient aspect of these tools is that they are modular; each individual model can be updated with advancements in research without needing to change the other models. The models together form a ‘workbench’ where simulation and risk assessment can be conducted.

The mammal density, acoustic, and sound exposure models can be modified, exchanged with other models, or made more robust without having to completely overhaul the support tool. Details on the three pieces of the decision support tool are provided in the subsections below, but a quick overview is given here of how these models work to estimate the impact of adding acoustic energy (hereafter referred to as sonar exercises) to the mammal’s marine environment.

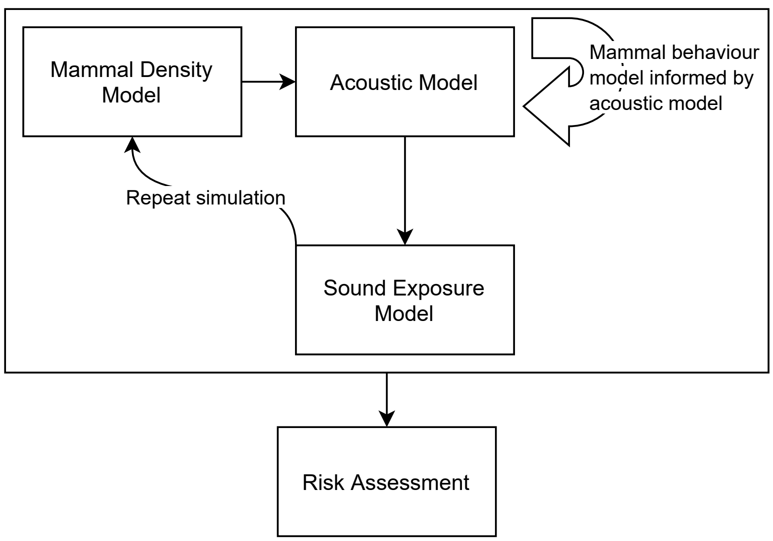

Figure 1: *Simple workflow of decision support tool. The models from Section 2 form a workbench for simulating marine mammals and their sound exposure. Everything from the workbench can then be fed into a risk assessment to form a decision support tool.*

The three models each have a specific function:

1. The mammal density model estimates where one would expect to find mammals and how many one would expect to find.

2. The acoustic model determines the sound pressure at all points in space for a given sonar exercise. Determines sound pressure level (SPL) and sound exposure level (SEL).

3. The sound exposure model relates the SEL to a probability of a mammal experiencing permanent/temporary damage or behavioural changes. This is done by combining the density and acoustic models to give the SEL of a simulated marine mammal.

Some decision support tools also include a fourth model: a marine mammal behaviour model. The behaviour model is used for simulating the path a mammal would take while being exposed to the sound levels predicted by the acoustic model, rather than assuming the mammal stays in one place during the entire exercise. The behaviour model is either separate from the three models above, or is included in the acoustic model.

Mammal locations can then be simulated from the density model in the sonar exercise region and the SEL can be calculated from the acoustic model. The SEL is a measure of how much sound the mammal is exposed to over time, and can be related via dose-response curves to effects on the mammal.

Figure 1 shows a simple workflow of how the different models feed into one another to produce an output that a risk assessment can be applied to. The following sections we detail each of the components of this diagram.

2.1 Mammal density model

A mammal density model:

- Estimates the probability of observing a mammal in a given region of space and time.
- Determines how mammals are distributed in a region.
- Allows calculation of the mean, variance, etc., of the number of mammals in region.

If mammal sightings[2] (visual or acoustic) over space and time are viewed as a pattern of points, then a point process model can be used to describe how those points are generated. For a point process approach one would estimate the intensity $\lambda(\vec{x})$ and probability $P\{N = n|\lambda, \theta\}$ of the random variable N in a region Ω with model parameters θ. The intensity can be interpreted as the expected number of points found per unit area or time (or both). The points $\vec{x}$ in space are elements of Ω. The random variable N refers to the number of mammals in a region A which is a subset of Ω ($A \subseteq \Omega$). Figure 2 provides a visual example of a model region Ω off the coast of Nova Scotia. Mammal sightings are represented by black dots in the ocean and a model fit over Ω would also allow for the calculation of statistics in any region $A \subseteq \Omega$.

If it is assumed that in a region A all mammal sighting locations are independent[3] and occur with constant intensity λ, then the number N of mammals in A is Poisson distributed with constant intensity λ. Figure 3 is an example of a Poisson distribution with constant intensity. More complicated models allow the intensity to vary over space instead of being taken as constant ($\lambda \to \lambda(\vec{x})$).

[2] All sightings are treated as equivalent for now. However, they are treated differently when incorporated in a density model to account for sampling effort.

[3] This assumption would likely be violated for mammals which typically travel in groups (or pods). This type of behaviour can be modelled with the addition of marks—see [6].

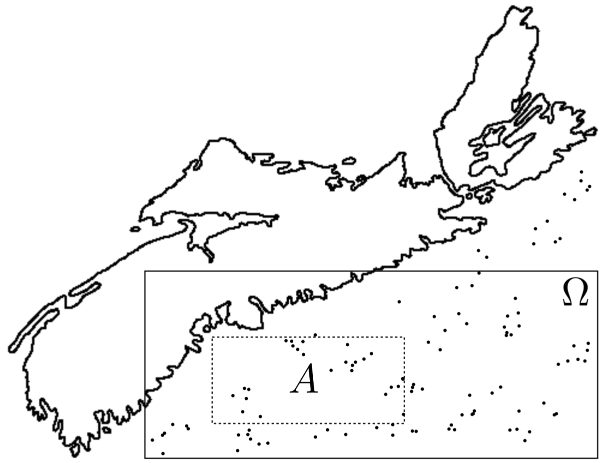

Figure 2: *Illustrative example mammal density setup. Mammal sightings are represented by black dots and the goal is to model the density of marine mammals in region Ω. Statistics such as the expected number of mammals, or the probability of observing 3 mammals, etc., in any region $A \subseteq \Omega$ can then be calculated.*

It should be noted here that any model using mammal sightings should have another component relating sightings to the true marine mammal density. This is because the true density cannot be modelled directly from observations since it cannot be known what proportion of the population is actually being observed. The observed intensity of detections can be viewed as a "thinning"[4] of the true intensity, i.e., $\lambda_{\text{obs}}(\vec{x}) = \lambda_{\text{true}}(\vec{x})P(\vec{x})$, where $P(\vec{x})$ is the probability of detecting a mammal at a point $\vec{x}$. A modelling framework then attempts to estimate the true intensity from the observed intensity. However, this caveat can be ignored for now without changing the purpose of the marine mammal density model—ultimately to estimate the number (and associated probability) of mammals in a given region.

In addition to accounting for detection probability the mammal sightings data needs to be "effort-corrected." That is, when sightings are made, the observer making the sighting is only looking at a small domain of the true mammal density in space and time. You cannot make mammal sightings in locations you are not observing. Part of the density modelling is to build up the true mammal density from these small snapshots while also taking into account detection probability.

Alternatively, one could estimate the density (mammals per square kilometre, for example) directly through distance sampling or habitat suitability models. Distance sampling has been the standard technique for estimating mammal density from a line transect survey [7]. The notation used in point-process models is adopted as it provides an

[4] One can think of thinning as flipping a coin, with probability $P(\vec{x})$ of showing heads, for each detection and keeping the detection if the coin came up heads.

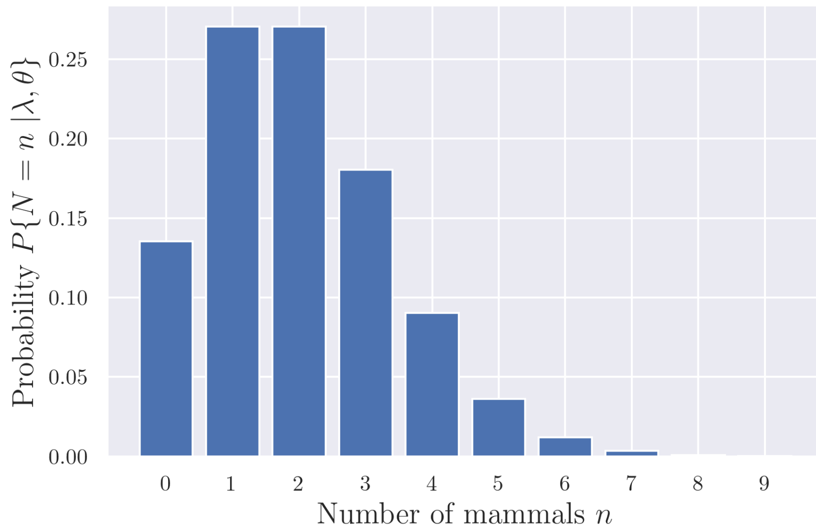

Figure 3: *Example distribution of the number of mammals, N, in a region A if N is Poisson distributed. Probability of observing n marine mammals over area $|A|$ with uniform intensity $\lambda|A| = 2$ and given model parameters θ.*

intuitive framework using conventional statistical terminology. However, the power of the point-process models is that they can take different sightings data types (line-transect, point-transect, opportunistic, etc.) and combine them into a single modelling framework by accounting for the sampling effort [6, 8].

In addition, the time dependency of mammal densities can be modelled by providing temporal regions T in combination with Ω. For example, Figure 4 shows the density of North Atlantic right whales for temporal regions $T = \{\text{August}, \text{September}, \text{October}\}$ off the coast of Nova Scotia. One can see that the spatial region Ω stops before Cape Breton island in the top right portion of each panel. The choice of temporal resolution is ultimately dependent on the data (whether you have data in a particular temporal region) and research has been done on the optimal choice for temporal regions in marine mammal densities [9]. However, the authors provide recommendations, rather than metrics or standards, for handling temporal regions of density estimation.

Currently, the Netherlands, the UK, and Norway rely on the mammal density estimates produced by the habitat suitability model (a type of density model) of Kaschner et al. [12]. In many cases these countries use the mammal density estimates from the UK Hydrographic Office (UKHO)—which are produced based on the methods of Kaschner et al. [12]. However, the US uses density maps from line-transect surveys if they exist in the area of interest, e.g., Bradford et al. [13], while relying on the habitat suitability model of Kaschner et al. [12] to extrapolate to areas without survey data [14–16]. Also available are the Ocean Biodiversity Information System's (OBIS) Spatial Ecological Analysis of Megavertebrate

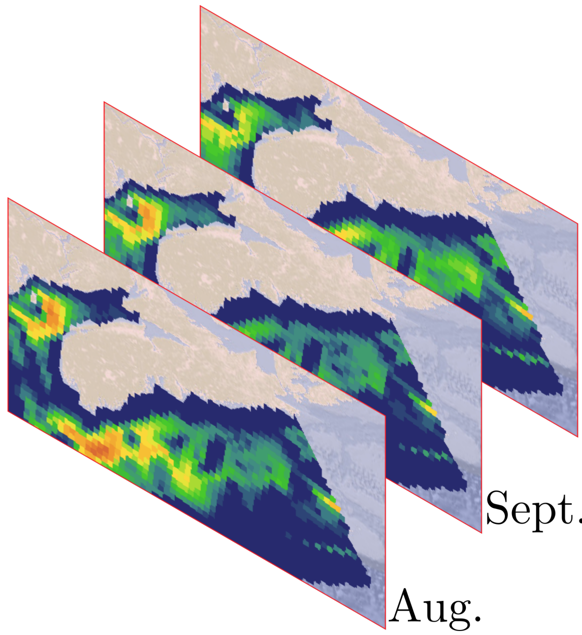

Figure 4: *Temporal aspect of marine mammal density. Different mammal densities for the North Atlantic Right Whale for temporal regions $T = \{August, September, October\}$. Density maps obtained from OBIS-SEAMAP on April 1, 2021 [10, 11].*

Populations (SEAMAP) density maps [17], from which Figure 4 was obtained.[5]

Statistical models have evolved since the 2006 paper by Kaschner et al. [12] and more advanced techniques have been implemented to estimate mammal densities. For example, Watson et al. have used Log-Gaussian Cox processes (a type of point process model) to model the density of Southern Resident Killer Whales off the west coast of Canada [6]. Harvey et al. use the, so called, G-star statistic to model multiple mammal densities—also off the west coast of Canada [18]. Mammal density models have also been estimated with line-transect survey data using distance sampling [19, 20]. Recently, density estimation from distance sampling has also been reformulated as a Log-Gaussian Cox process [8].

[5] Model outputs served through the Model Mapper are licensed under the CC-BY sharing policy. See `https://seamap.env.duke.edu/models/termsofuse/USECGOM/2015`. Last access date: 2022-02-01.

Density models have a wide range of applications, but existing decision support tools have two uses for mammal densities:

1. As an added layer to inform decision makers of hot spots, and
2. As a distribution to draw from for Monte-Carlo simulations[6] which allow the user to do quantitative risk assessment.

An example of the first case is Norway's Sonate tool [21] which uses a mammal density model with a "guidelines" layer for informing decision makers of mammal hotspots to avoid. However, some tools, like that described in Reference [22], use the density model to do Monte-Carlo simulations of marine mammal locations to determine the distribution of SEL in the population area (simulations are repeated until the output distribution satisfies some convergence criteria). Risk assessment can then be done on the output SEL distribution.

2.2 Acoustic and behaviour model

The acoustic and behaviour model:

- Determines sound pressure at all points in space for a given collection of sound sources.
- Incorporates mammal behaviour as a function of sound exposure (in some cases, but it is not required).

To determine the impact of a sonar exercise on marine mammals an acoustic model is needed to calculate sound pressure at all points $\vec{x}$ in the region Ω. This gives a sound pressure field that assigns a sound pressure level in decibels (dB) to each point in the region caused by a collection of sound sources. The SPL at a point $\vec{x}$ from n incoherent sound sources is given by [23],

$$\mathrm{SPL}(\vec{x}) = 10\log_{10}\left[\frac{1}{p_0^2}\sum_{i=1}^{n} p_i(\vec{x})^2\right]\mathrm{dB} \tag{1}$$

where p_0 is the reference pressure (taken to be 1 μPa underwater) and $p_i(\vec{x})$ is the pressure, in μPa, at point $\vec{x}$ caused by sound source i. The values of $p_i(\vec{x})$ are what is determined by the acoustic model.

[6] Monte-Carlo simulation is a mathematical technique to estimate the distribution of random events and provide numerical results based on the distribution.

The cumulative effect of sound pressure over time on a mammal is captured by the SEL. If the sound pressure a mammal is subjected to along its path over time t is $p_{\mathrm{path}}(t)$ then the SEL between times t_0 and t_1 is given by [23],

$$\mathrm{SEL}(t_0, t_1) = 10 \log_{10} \left[\frac{1}{E_0} \int_{t_0}^{t_1} p_{\mathrm{path}}(t)^2 \, \mathrm{d}t \right] \mathrm{dB} \tag{2}$$

where $E_0 = 1\ \mu\mathrm{Pa}^2 \cdot \mathrm{s}$ is the reference underwater sound exposure.

The acoustic model sometimes includes a marine mammal behaviour model which allows one to simulate the SEL experienced by a marine mammal as it moves through the sound field. These models need not be intertwined, but are often presented in the literature as a single model. For example, as new marine mammal behaviour models are developed, they can be swapped in to better capture the sound exposure and harm inflicted on the mammal. Harm can also include long-term effects on overall population, but this is currently an active area of research [24]. For example, the Netherland's tool, SAKAMATA (Sea Animal Kind Area-dependant Mitigated Active Transmission Aid) [25], models the mammal behaviour in response to sound exposure and uses ALMOST (Acoustic Loss Model for Operational Studies and Tasks) [26] for modelling acoustic propagation. Details of SAKAMATA's mammal behaviour model are given in [25].

One of the first models to include both sound propagation and mammal behaviour was AIM (Acoustic Integration Model) [27] developed in 2002 by the Office of Naval Research (ONR). Following this, the Naval Research Laboratory (NRL) initiated a "multidisciplinary research and development program" called the Effects of Sound on the Marine Environment (ESME) [28]. Within ESME is the Marine Mammal Movement and Behaviour (3 MB) model [29]. Finally, the SAFESIMM (Statistical Algorithms for Estimating the Sonar Influence on Marine Megafauna) model [22] was developed as part of the Environmental Risk Management Capability (ERMC) system sold by BAE Systems and has been used to plan sonar activities [30].

2.3 Sound exposure model

A sound exposure model:

- Relates sound exposure to TTS and PTS.
- Determines the probability of a threshold shift according to dose-response curves.
- Allows for the quantification of the impact on mammals from sound sources over time.

The sound propagation and behaviour models determine the SEL that a mammal would receive given that it was in the exercise zone at a specific time and place. The mammal density model estimates the probability of the mammal being at that specific time and place and the behaviour model determines the path the mammal takes when exposed to the sound. The cumulative sound exposure over the mammal's path gives the SEL. Figure 5 depicts a single (illustrative) simulation example of a path traced out by a whale exposed to sound emitted by an active sonobuoy.

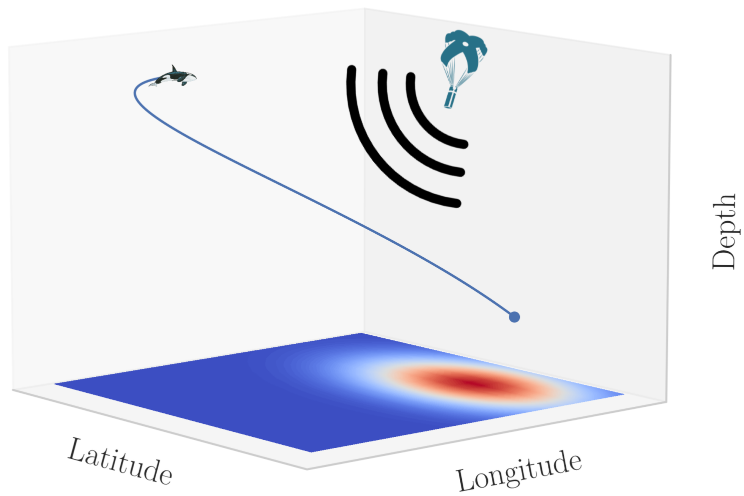

Figure 5: *Graphical depiction of the sound propagation and mammal behaviour model portion of risk assessment. The density map at the bottom of the figure indicates mammal hot spots in red. Mammal locations are simulated from this density map (indicated by the blue dot) and trace out a path (blue line) when exposed to sound propagation.*

The final piece to the decision support tool is to relate the calculated SEL to a probability of causing harm to the mammal. Harm to the mammals due to a given SEL can be assessed by the probability of PTS and TTS [31–33] from, so-called, "dose-response" curves [34–36]. Since the initial work, there have been updated recommendations for sound levels thought to cause TTS/PTS [37]. Although TTS/PTS SEL threshold values exist for many species, dose-response curves do not. However, further work into providing dose-response curves for TTS/PTS onset would add more flexibility to a risk assessment and improve calculations of impact from active sonar [38].

Figure 6 gives an example of what a dose-response curve for PTS would look like. The shape of the dose-response curves for TTS and behavioural changes would look similar, but shifted to lower SEL values. The reason for using SEL as an indicator of harm is, according to NOAA, TTS/PTS onset for non-impulsive sound sources (like military sonar) is gauged based on the received SEL [14–16]. The SEL to the mammal at a given time also partly drives their behaviour model through a similar dose-response curve for the probability of a behaviour change.

Aside from immediate impacts, like TTS/PTS, there is ongoing research into quantifying long term impacts from sound exposure—changing feeding or migration patterns, for example. The US Navy's Protective Measures Assessment Protocol (PMAP) [39, 40] uses

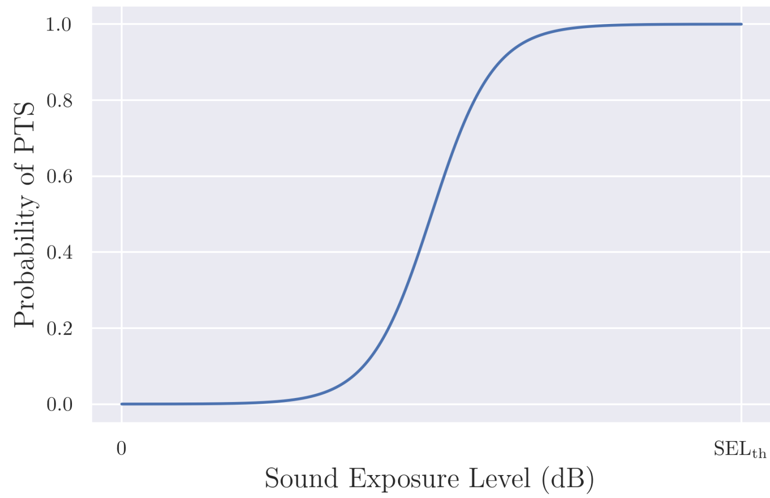

Figure 6: *Illustrative example of a dose-response curve for the probability of PTS due to SEL. The probability is zero at zero sound exposure and increases gradually until there is a guaranteed impact at some threshold* $\mathrm{SEL}_{\mathrm{th}}$.

the Navy Acoustic Effects Model (NAEMO) for sound propagation[7] [16] and is developing long-term effects models under the Population Consequences of Acoustic Disturbance (PCAD) model, which serves as a conceptual model, rather than a predictive one [41]. This is, PCAD was a conceptual framework and not a tested means to calculate the population consequences. Further research with the PCAD framework has resulted in the Population Consequences of Disturbance (PCoD) model, which has been used in the UK, Netherlands, Germany, Canada, and the US [24, 42].

However, some decision support tools do not relate sound exposure to marine mammal impacts. NATO's Integrated Decision Aide (IDA), for example, uses a sound propagation model to visualize the sound impact area on top of mammal density layers in a geographic information system (GIS) framework to aide in decision making without calculations of TTS/PTS [43].

2.4 Decision support tool summary

Table 2 summarizes some of the available decision tools and their underlying models. The table lists the mammal density model, the acoustic model, and the behaviour model in each case while leaving out the exposure model. This is because all tools that incorporate a risk assessment calculation do so through relating SEL to the probability of TTS/PTS onset. Instead, the comments column includes whether or not the tool includes such a risk calculation. It should be noted that the number of TTS/PTS exposures is not the only way to assess risk and that models like PCoD serve as alternative (or additional) methodologies.

[7] However, the US sometimes uses only AIM for their acoustic effects model [14, 15]

These tools are roughly divided into two categories: those that attempt to account for a number of TTS/PTS exposures through simulation, and those that do not. Norway's Sonate and NATO's IDA only provide overlaid layers in a GIS setting for decision support and do not provide a calculated risk assessment. However, the UK, NL, and US, use their acoustic models (sometimes in combination with a behaviour model) to estimate the SEL for mammals in the operational zone during sonar exercises. The SEL is then related to a probability of TTS/PTS through dose-response curves or TTS/PTS onset thresholds.

The US does not strictly rely on PMAP for its marine mammal mitigation. They also use NAEMO, without the PMAP framework for risk assessment—sometimes including mammal behaviour models. This may reflect a benefit of the modular set up of these decision support tools where one can mix and match different models depending on the purpose or requirements of an exercise.

It is worth repeating all tools rely on a modular setting where each individual model can be swapped out or replaced as new research and technology becomes available. The tools as presented are based on the available research at the time of their development. Each piece is itself a large and expanding area of active research. Marine mammal mitigation tools attempt to combine the efforts of multiple fields into a single support aide—which is not an easy problem to solve.

Table 2: *Breakdown of decision support tools and their underlying models. List is not exhaustive and is based on available information. In particular, the US does not rely on a single tool or model for their risk assessment [14–16]. A × symbol means that model is not included in the tool.*

Organization (Tool)	Mammal Density Model	Acoustic Model	Behaviour Model	Comments
Norway (Sonate)	Habitat suitability (UKHO) [12] Russian density maps Directorate of Fisheries observations	×	×	Density and regulation guidelines layers overlaid. No direct risk calculations or acoustic modelling.
NATO (IDA)	Included, but information not available	Included, but unnamed	×	No details about underlying models. Density and acoustic layers overlaid. No simulation or calculations of TTS/PTS.
UK[8] (ERMC)	Habitat suitability (UKHO) [12,17]	Included, but unnamed.	SAFESIMM [22]	Risk assessment through TTS/PTS [31–33].
NL (SAKAMATA)	Habitat suitability (UKHO) [12]	ALMOST [26]	Included – built into SAKAMATA [25]	Risk assessment through TTS/PTS [31–33]
US[9] (PMAP, NAEMO)	Line-transect surveys (for example, [13]) Habitat suitability (UKHO) [12]	AIM [27] CASS/GRAB [44,45]	3 MB [29]	Risk assessment through TTS/PTS [31–33]. Exploring long term impacts through PCAD [41]. Behaviour model not always used.

[8] Not explicitly stated as tool of UK Navy, but used in planning sonar exercises [30].
[9] NAEMO is the underlying impact model while PMAP generates reports for regulation compliance.

3 Risk assessment

The risk of harm to marine mammals comes from uncertainty. Mathematically, risk is not bad outcomes, but our uncertainty in bad outcomes. Disastrous, but certain, events have no risk because they are guaranteed to happen. Risk management is about identifying the disastrous, but uncertain, events and determining what uncertainties are inherent in our predictions of those events. The sources of these uncertainties are called risk factors and can come from, for example, imperfect information or model parameter estimation. Ultimately, uncertainty is characterized by statistical distributions that serve as inputs to risk measures that quantify the risk of disastrous events.

The risk management strategy for the decision support tool is to identify and quantify the uncertainties inherent in model predictions and the uncertainties within the model parameters themselves. Not only are statistical measures like the mean and variance in the distribution of the number of marine mammals in a given region important, but also statistical measures associated with the model parameters that estimate this distribution. Even the model parameters can have their own distributions. The “risk” to marine mammals due to model parameters comes from potentially bad decisions made based on model outputs.

Model risk may also appear in the acoustic models and the sound exposure models for determining impacts on marine mammal species. The uncertainties in the density model are compounded by the uncertainties in the acoustic model and sound exposure models as one model’s output acts as the input to the next and ends up in the final distribution of SEL experienced by the simulated mammals. This final distribution becomes the input to the risk measures. Risk measures, like the ones covered in this section, are used to quantitatively determine worse case scenarios predicted by the models in combination with the uncertainties inherent in the models.

Effective risk management has to account for risk within the model itself and not just the risk the model attempts to capture. Otherwise, one may end up relying on poor quality models for important decisions, that can have disastrous consequences. A famous example from quantitative finance is from David Li’s work on the Gaussian copula [46] and its misuse by the finance industry. The Gaussian copula allows one to easily model very large dimensional multivariate distributions; it was used to model the correlations between defaulting mortgages. However, the model failed to factor in changing correlations based on market conditions and left complicated financial derivatives based on mortgages improperly priced and evaluated for risk which contributed to the 2008 financial crisis.

An example like the above which could happen in our risk assessment is if a mammal behaviour model is used which over estimates the swim speed of a given mammal. The behaviour model would then under estimate the SEL and, thus, under estimate the onset of TTS/PTS. Improper use of mathematical models can have disastrous consequences if they are not properly backtested to make sure they are doing what you want them to do.

The goal of the integrated decision tool is to quantify the risk of harming marine mammals with active sonar in order to make decisions which adhere to marine mammal mitigation policy. A policy layer could take the risk assessment as input to tell operators which areas they are allowed to do sonar operations in and which sonar devices are allowed to be used. The risk calculations will be integrated into a policy layer which also takes into account marine protected and conserved areas, critical habitats, active sonar avoidance zones, etc., which further restrict the possible areas of operations in order to avoid propagating sound into these sensitive areas. Also, the policy layer could be dynamic and change over time or by coast—different protected species in different coasts may necessitate different mitigation policies over time.

3.1 Properties of risk measures

There are a number of ways of quantifying the uncertainty of adverse events. There will be some distribution of outcomes of some random event, say stock returns or number of marine mammals in a given region, and the goal is to assign a number to the distribution which captures the risk inherent in that event. The distribution of the number of marine mammals in a given region is used as a proxy for the distribution of harm due to sound exposure in this section to simplify the discussion. The risk is in our uncertainty of how many mammals are in a given region.

Researchers have defined five key properties a risk measure might have [47] with a measure satisfying all five being called a coherent risk measure. These are reasonable properties a financial risk measure may have, but this may not be the case for risk management in other fields—like marine mammal mitigation. These five properties are defined as follows.

Let X be a random variable, say stock returns or number of marine mammals in a given area, which belongs to some appropriate space of measurable functions $\mathcal{X}$. Then a coherent risk measure $\mathcal{R}$ is a functional, which maps random variables $X \in \mathcal{X}$ to the real numbers $\mathbb{R}$, that satisfies the following five properties:

Normalization $\mathcal{R}(0) = 0$

Monotonicity If $X_1, X_2 \in \mathcal{X}$ and $X_1 \leq X_2$ a.s.,[10] then $\mathcal{R}(X_1) \geq \mathcal{R}(X_2)$

Sub-additivity If $X_1, X_2 \in \mathcal{X}$, then $\mathcal{R}(X_1 + X_2) \leq \mathcal{R}(X_1) + \mathcal{R}(X_2)$

Positive homogeneity If $a \geq 0$ and $X \in \mathcal{X}$, then $\mathcal{R}(aX) = a\mathcal{R}(X)$

Translation invariance If $a \geq 0$ and $X \in \mathcal{X}$, then $\mathcal{R}(X + a) = \mathcal{R}(X) - a$

Normalization means that the risk associated with no assets is zero. Similarly, the risk of sonar exposure to zero marine mammals should also be zero.

[10] Almost surely: this means $P(X_1 \leq X_2) = 1$ for probability measure P defined on our probability space.

Monotonicity implies that if there are two random variables and one almost surely has worse outcomes than the other, then it will carry more risk. For example, two stocks where one has strictly worse returns than another—it will naturally be a riskier stock to hold. Alternatively, two regions in space where one has a strictly higher probability of encountering any given number of marine mammals—this region would have a higher risk of harming a marine mammal with active sonar.

Sub-additivity captures the benefit of diversification. A portfolio of two stocks will be less risky than the combination of two portfolios each built from a single stock. It is not obvious that this condition could extend to all financial objects, and even other areas of risk management. For marine mammal mitigation, sub-additivity could appear when planning a sonar exercise in two different location at the same time. The risk posed by the combined two operations could possibly be greater (rather than less) than the risk of each operation taken by itself due to sound from both sources propagating in the same area or by forcing marine mammals from one operation area to the other.

Positive homogeneity would imply doubling a position in a stock would double your risk. For marine mammal mitigation, the idea would be that risk scales with the number of marine mammals exposed to sonar. However, due to spatial inhomogeneity this condition may not be a strict equality.

Translation invariance says that making a portfolio of a deterministic variable, say cash or a riskless asset, to a stock will reduce the risk to the portfolio by the value of the riskless asset. One needs to be careful with this condition because of the signs of the variables being added together. For marine mammal mitigation, adding a guaranteed whale to an area exposed to sound should change the risk assessment based on the predicted distribution of mammals in the area and where the whale was detected in the operation area. The risk should increase if the whale is sufficiently close to the sound source, and decrease if the whale is far from the sound source. So, translation invariance may add or subtract from the risk rather than being a guaranteed reduction.

These conditions are not necessary for the definition of a risk measure (even in finance), but motivates the idea to define a risk measure which satisfies a number of properties one expects to hold for their application.

3.2 Risk measure examples

The following subsection provides several examples of risk measures and their applications. Also, a description of their advantages and disadvantages. The main takeaway being that one needs to define a risk measure which captures the risk they are trying to quantify and this is often completely dependent on the application.

3.2.1 Expected value

The simplest risk measure would be the expected value, $E[\,\cdot\,]$, of some cost function which is dependent on a random variable. For example, in credit risk analysis the expected loss captures the financial institution's expected loss on a loan when the loan carrier defaults on their payments. The expected loss is given by,

$$\begin{aligned} E[\text{Loss}] &= P(\text{Default}) \cdot \text{Loss}(\text{Default}) + P(\text{Non-Default}) \cdot \text{Loss}(\text{Non-Default}) \\ &= P(\text{Default}) \cdot \text{LGD} \cdot \text{EAD} \end{aligned} \tag{3}$$

where LGD is the loss given default and EAD is the exposure at default. Note that the impact of a non-default is zero, so it does not contribute to the expected value. However, expected value tells you nothing about unexpected losses. That is, it does not tell you anything about worse-case scenarios where an institution may be exposed to a very unlikely default, but a disastrous impact if the loan were to default. One needs to include some measure of the variance of the distribution of losses to attempt to account for unexpected losses. Additionally, the expected value of two loans may be the same for very different loss distributions.

Using only the expected value as a risk measure is known as "risk neutral" in finance. This is because a risk neutral person would assign the same value to two games where one guarantees a payout of one dollar and another pays out a hundred dollars 1% of the time and zero dollars 99% for the time. Obviously, the second game is significantly riskier, but a risk neutral person would view them as the same (they both have expected value of one dollar). That being said, the expected value satisfies the conditions of a coherent risk measure.

A way to incorporate unexpected events is to include the variance of your loss distribution, or other variables derived from the variance of the distribution.

3.2.2 Variance

Including the variance of the loss distribution as a risk measure allows accounting for more than just the expected losses—often one is more interested in attempting to mitigate very unlikely, but disastrous events. The variance gives the expected squared deviation from the mean and is expressed as

$$Var[X] = E[(X - E[X])^2] \tag{4}$$

This would be a first step towards integrating uncertainty into risk assessment. Similarly, the standard deviation (square root of the variance) would serve the same role.

In finance, the standard deviation of an asset's return is referred to as volatility. Volatility is often quoted as a proxy for risk to give one an idea of the size of up or down price movements over a given time period. Assets with larger volatility are more likely to see larger down movements, but also more likely to see larger returns. Hence, large volatility (or standard deviation/variance) is not necessarily a bad thing.

Unfortunately, variance (or standard deviation) is not a coherent risk measure because it fails to be translation invariant since $Var(X + a) = Var(X)$ and not $Var(X) - a$, where a is a constant. So, variance would be a poor choice for a risk measure if it is believed a form of translation invariance should exist (as discussed in Section 3.1) in marine mammal mitigation when incorporating detections of mammals in the operation area into the risk assessment.

However, variance is used as a proxy for risk in Markowitz's seminal work in portfolio optimization theory [48]. In this set up, an investor chooses the makeup of their portfolio which minimizes the variance of the portfolio returns for a given portfolio return. At the time, this framework was one of the first that gave decision makers a way to build portfolios that balanced their returns for a given level of risk.

Since Markowitz published his portfolio theory in 1952, more sophisticated risk measures have been developed that give decision makers some confidence level that losses will exceed some threshold only a given percent of the time. The value at risk, covered in the next subsection, is one such risk measure. The point being that the choice of risk measure (variance versus value at risk, for example) will depend on the application and the risk management strategy.

3.2.3 Value at risk

Since increasing variance would imply increasing probability of both good and bad events, one may want a risk measure associated with how bad can events be and how frequent they are expected to happen. One way is to analyze the quantiles of our distribution—specifically the side of the distribution associated with bad events. For a random variable X with probability measure P, the $\alpha \in (0, 1)$ quantile, $Q_\alpha(X)$, is defined as,

$$Q_\alpha(X) = \inf\{x : P(X \leq x) \geq \alpha\} \tag{5}$$

So, if X were stock returns, then $Q_\alpha(X)$ would give the return x which is greater than α percent of all possible returns. For this example, one can then use the quantile as a risk measure for determining, say, the return which is at least as bad as 1% of all returns—$Q_{1\%}(X)$. The risk measure in that case is called value at risk (VaR) and is defined as,

$$\mathrm{VaR}_{1-\alpha}(X) = \inf\{x : P(X \leq x) \geq 1 - \alpha\} \tag{6}$$

which is the same definition as the quantile with a reinterpretation of α (99% VaR is the 1% quantile). The definition of VaR above is assuming the left tail of the distribution of X is associated with the bad outcomes. So, one needs to be careful to use the appropriate definition depending on which side of the distribution the “risks” are. For example, negative returns are the concern in finance (left tail) while in marine mammal mitigation the higher number of mammals in a region (right tail) is of concern.

VaR and α have a similar interpretation to confidence intervals and confidence levels. The 95% VaR value ($\alpha = 5\%$) tells us that with a 95% confidence level that only 5% of losses will exceed the 95% VaR. Similar to how 95% of confidence intervals calculated at the 95% confidence level will contain the true value of some unknown parameter.

However, VaR is not a coherent risk measure because it does not always satisfy the subadditive property. Despite this fact, it is widely used in finance as a default risk measure because it is easy to understand and easy to calculate.

Related to VaR is exceedance probability. The exceedance probability Θ is defined as $\Theta(X, L) = P(X \leq L)$ for random variable X and loss threshold L (the definition here implies losses are in the left tail of the distribution). However, like VaR, the exceedance probability does not tell you about what losses to expect when they exceed the threshold.

3.2.4 Expected shortfall

The major downside of VaR is that it tells you nothing about outcomes worse than the VaR—only that they occur less than $1 - \alpha$ percent of the time. Expected shortfall, which is the expected loss given that the losses are in excess of the VaR, can account for this. The definition of expected shortfall is then,

$$\mathrm{ES}_{1-\alpha}(X) = \frac{1}{\alpha} \int_0^\alpha \mathrm{VaR}_{1-\gamma}(X) d\gamma \tag{7}$$

One can then think of expected shortfall as averaging the losses in excess of the associated VaR value. If the underlying loss distribution X is continuous then expected shortfall can be written as,

$$\mathrm{ES}_{1-\alpha}(X) = E[\mathrm{Loss} \mid \mathrm{Loss} \geq \mathrm{VaR}_{1-\alpha}(X)] \tag{8}$$

Since expected shortfall can be written as a conditional expectation it is sometimes referred to as conditional value at risk (CVaR). Expected shortfall is able to then answer the question of how bad the expected losses can be when things go “very bad.” Very bad being defined as losses in excess of the VaR risk measure. Even though expected shortfall is built from VaR, it is a coherent risk measure.

3.2.5 Spatial-temporal risk measures

Recent work has explored risk measures which take into account the spatial-temporal properties of risk over a given region [49–51]. Applications would include any loss or damage functions dependant on spatial-temporal areas driven by random effects—say, modelling spatial dependency of credit default, or climate related disasters such as wildfires. Direct application has been made in the area of urban design [52].

The basic idea is to aggregate the risk measures (for example, the ones discussed in the previous subsections) over a spatial-temporal domain and then normalize the results so that one can compare the normalized risks between different sized spatial-temporal regions. One application for marine mammal mitigation would be in comparing the risk posed in different sized spatial regions for a given sonar activity. It may not be necessary, but the literature provides a way to do this if it is required.

3.3 Summary of risk measures

This subsection summarizes the risk measures that have been covered with two examples: a continuous distribution of daily stock returns, and a discrete distribution of marine mammal population. In both cases the expected value, variance, value at risk, and expected short fall are calculated. The variance is presented in the form of one standard deviation[11] from the mean towards the tail where the losses are located. The value $\alpha = 0.01$ is used for the 99% VaR and expected shortfall.

In Figure 7 the losses are in the left tail of the distribution, so our risk measures attempt to quantify very unlikely, but possible, extreme losses. The mean is 0 and the variance/standard deviation is 1, since the distribution is the standard normal. The 99% VaR is then the 1% quantile in the left tail which says there is a 1% probability the return will be less than -2.33, or that one should expect a loss as bad as -2.33 once every hundred trading days. Expected shortfall then quantifies returns worse than the VaR value to give -2.67. So, the expected daily loss in excess of the associated VaR is -2.67.

Figure 8 presents the risk measures for an example of a discrete distribution—expected mammal population in a given region following a Poisson distribution. Since more mammals are viewed as the “bad” outcomes,[12] the right tail of the distribution is where the risk lies. The expected number of mammals is 4 and one standard deviation from the mean is 6. The 99% VaR says to expect to see at least 9 mammals 1% of the time and the expected shortfall says the expected number in excess of the VaR is $\approx$ 10 mammals.

[11] Not the same as the variance, but is one way of comparing the variance risk measure to VaR and expected shortfall.

[12] More mammals are potentially exposed to harm from active sonar in high population areas.

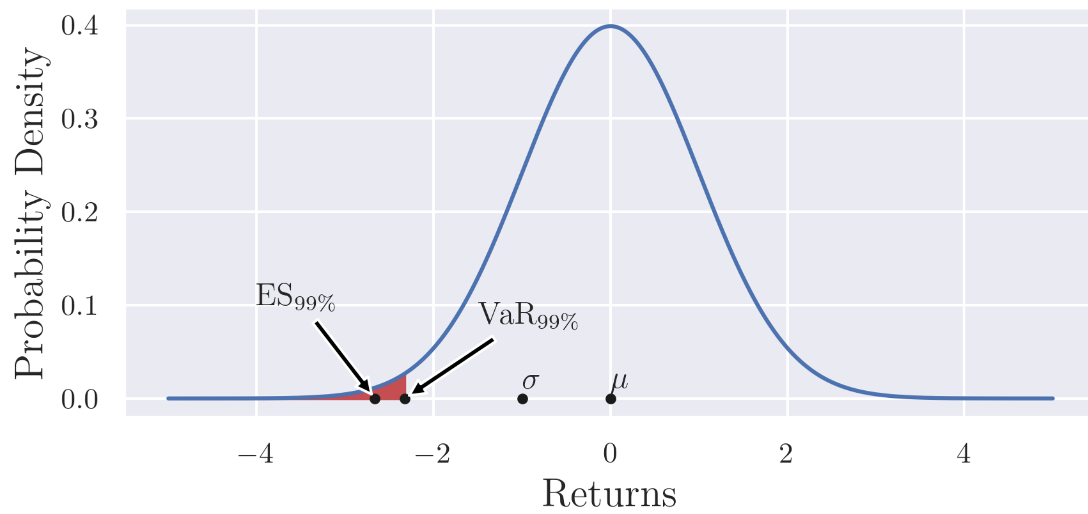

Figure 7: *Risk measures for a continuous distribution. The standard normal distribution $\mathcal{N}(0, 1)$ is used to represent daily stock returns in dollars. Black dots are labelled for the expected value μ, one standard deviation σ, the 99% VaR, and the 99% expected shortfall. The shaded red region covers the worst 1% of returns.*

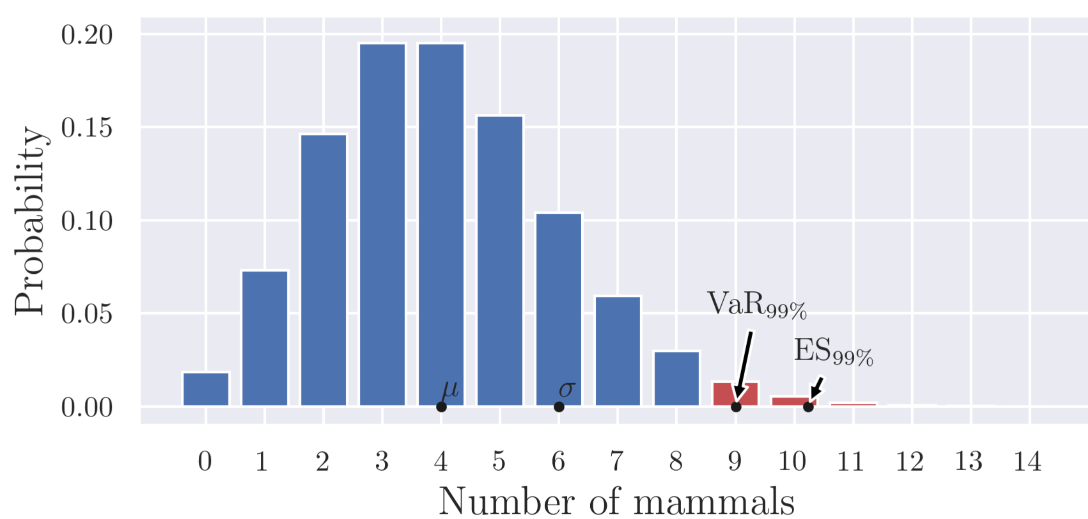

Figure 8: *Risk measures for a discrete distribution. The Poisson distribution with mean 4 is used to represent the possible number of mammals in a given region. Black dots are labelled for the expected value μ, one standard deviation σ, the 99% VaR, and the 99% expected shortfall. The shaded red bars cover the worst 1% of mammal numbers.*

These risk measures attempt to determine, quantitatively, the impact of rare situations in a systematic way to compare the results across different distributions. Ultimately, these risk measures are applied to distributions that are calibrated from data and are then based, in some sense, on the worst outcomes that have actually been observed. What about the extremely rare events which have not, or cannot, be observed? How does risk change during extreme financial market or environmental conditions? Decision makers are still vulnerable to these so called “black swan” [53] events that are not captured by our risk measures. This is why backtesting and stress testing are important aspects of model validation—how bad are our models during very rare events? In the end, this type of risk evaluation should be one piece of a larger strategy since there is a limit to what can be done purely from mathematical modelling.

4 Data requirements

A decision support tool for marine mammal mitigation would be calibrated to historical data and can be updated as new data is collected. The tool itself would rely on the collection of both mammal sightings data and environmental covariates and these data are integral to the success of the DCS task. The tool needs data to function, but the necessary data are complicated by multiple factors.

For mammal detections, effort correction must be incorporated with opportunistic sightings within the density models and combined with transect survey data where appropriate. In addition to sightings data there are environmental covariates which need to be collected concurrently with the sightings to feed into the density model. Leveraging real (or near real) time data streams would also allow for updated risk assessments as the sonar exercise date approaches.

4.1 Opportunistic and survey sightings

A key part of marine mammal density estimation is accounting for the effort, via effort-correction, used in collecting the data to calibrate the model. If one is using purely presence data then the model will be heavily biased towards assigning a relatively higher density to regions where the data was collected. This would ignore the presence of marine mammals in regions not covered by the data collection effort. Effort-correction is a way to resolve this issue by weighting presence data to reflect that there was little to no effort in some places, but higher effort in others when making detections.

This problem can be further complicated when attempting to account for, and combining, the effort of multiple different observer categories—ships, enthusiasts, or satellites, for example. In some cases the effort can be calculated exactly if the details of the observer's path and field of view are known. The calculated effort is then used to approximate an "effort surface" over the region in which mammal density is being modelled. Perfect effort would imply a uniform value (based on the size of the spatial-temporal region) across the entire spatial-temporal region, as opposed to regions of zero effort where there was no attempted observation.

Intertwined with the effort surface is also a probability of detection surface given a level of effort. That is, one also models the fact that an observer could still not detect a marine mammal even with perfect effort in a given region. Covariates can then be included in approximating the effort and probability of detection surface—observer type, visibility index, distance from observer to detection, for example. Even crude approximations to the effort surface can yield substantial improvements to the accuracy of mammal density estimates [6].

Aside from opportunistic sightings there are also line transect surveys that can be included in the density estimation. Recent work with Log-Gaussian Cox models has been done for effort-corrected opportunistic sightings [6] and also line transect surveys [8]. Integrating these two techniques together would leverage both types of data. Density estimation has been done using point transect surveys [54], but has not been integrated into the Log-Gaussian Cox model framework yet. Since the decision support tool is meant to mitigate the harm to all marine mammals, the data to calibrate each density model may come from multiple different sightings data sets.

4.2 Environmental covariates

The mammal density model can be calibrated using effort-corrected presence and presence-absence data, but environmental covariates can also be included in the model. The choice of covariates differs by the model, but several examples are provided from the literature. Bathymetry [55], distance to the coast, ice concentration [56], and sea surface salinity [57] were used to model the density of polar bears, Atlantic walrus, and ringed seals in the arctic [58]. Sea surface temperature and chlorophyll-*a* [59] were used in the previously mentioned work by Watson et al. in modelling the density of Southern Resident Killer Whales off the west coast of Canada [6]. The habitat suitability models of Kaschner et al. used bathymetry [60], mean annual surface temperature [61], mean annual distance to ice edge,[13] and distance to land as covariates [12]. Covariates are not necessarily species specific, but may have higher predictive power for different species.

All of these covariates (and more) were used in a generalized additive model by Harvey et al. to model nine different mammal densities and they divided the covariates into static, dynamic, and climatological categories, which are summarized below[14] [18]. Details and citations for the rationale behind including these covariates in their model can be found in Harvey et al. [18].

Table 3: *Static covariates.*

Covariate	Units
Latitude and Longitude	degrees
Bathymetry	m
Slope of ocean floor	degrees
Benthic terrain ruggedness	proportion
Distance from coast	m
Distance from continental shelf	m
Distance from high current areas	m

[13] Data obtained from US National Snow and Ice Data Center. Exact data set not listed.

[14] Exact data sets not listed. Sources include: Raincoast Conservation Foundation, SciTech Consulting and Living Oceans Society, DataBC, National Oceanic and Atmospheric Administration CoastWatch, World Ocean Database.

Table 4: *Dynamic covariates.*

Covariate	Units
Tidal current	m/s
Sea surface temperature	°C
Chlorophyll-a concentration	mg/m^3
Wind	m/s
Sea height absolute	m
Sea height deviation	m

Table 5: *Climatological covariates.*

Covariate	Units
Temperature	°C
Salinity	ppm

4.3 Real and near real time data

The integration of historical data layers with real (or near real) time data streams is critical for developing a data management strategy that can be used for marine mammal mitigation. The data streams from different sensors could even be sending data back at different time intervals. Some more frequent than others. Even the formats of this data would not necessarily be the same. The DCS tasks, mentioned in the introduction of this Report, are not just the development of a decision support tool, but also include the development of automated and autonomous detection systems for marine mammals. These systems feed into the historical data layers, but also allow for leveraging the data streams in real (or near real) time by updating existing risk assessments.

In order for the tool to be used to perform updated risk assessments after the initial planning phase, the tool will require this sensor data to be fed into it. This can be done if an appropriate density model is used that allows the calculation of probabilities conditional on new observations. These conditional probabilities can then, effectively, be used with the risk measures from Section 3 to give updated risk assessments given new information.

5 Concluding remarks

The models covered in Section 2 form the basis for a workbench to simulate the exposure to sound of marine mammals. The combined models become a decision support tool when the resulting distributions, parameters, and variables from the workbench are fed into a risk assessment which may include measures from Section 3. Risk measures were applied in Section 3 to only the distribution of marine mammals in a given region, but these measures can be applied to any distribution obtained from the workbench—such as the distribution of TTS/PTS for a given mammal after sufficient simulations have been performed.

Figure 9 charts the workflow of relevant data layers and model parameters that enter into each model component of the workbench. It is worth stressing that this Monte-Carlo simulation workflow is repeated until the full distribution of harmful outcomes is clear. Ultimately, everything is then passed to a risk assessment model that can then identify mitigation procedures and dynamic policy to decision makers based CAF-accepted criteria. Due to the modular nature of the workbench, if new distributions or variables are needed in the future for risk mitigation then they can be included by modifying the appropriate model.

After taking existing density, acoustic, behaviour, and exposure models and connecting them via a workflow, as depicted in Figure 9, different risk measures can be explored. An initial risk assessment of the number of impacted mammals can then be done by multiplying the output of two risk calculations:

1. Risk measures applied to the density model which provide a worst-case population scenario for an ensonified area.
2. Risk measures applied to the distribution of simulated mammals in combination with the acoustic and exposure models provide the proportion of mammals in the ensonified area impacted given the risk criteria (TTS, PTS, etc.)

Further work is also being conducted to incorporate real-time detections into this risk calculation to update the risk assessment using the most current information. Integrating the real-time detections would be motivated by the properties of risk measures discussed in Section 3.1 to ensure that the final risk assessment measure has properties which make sense for marine mammal mitigation.

Once the ability to assign risk to a given area is obtained then the decision support tool can include optimization algorithms to determine the optimal location for sonar operations that minimizes some risk criteria. The algorithms could also include relaying which sonar devices can and cannot be used in specific regions based on impacts to marine mammals determined by acoustic modelling using device specific properties. These are just examples of some questions that the decision support tool can help answer.

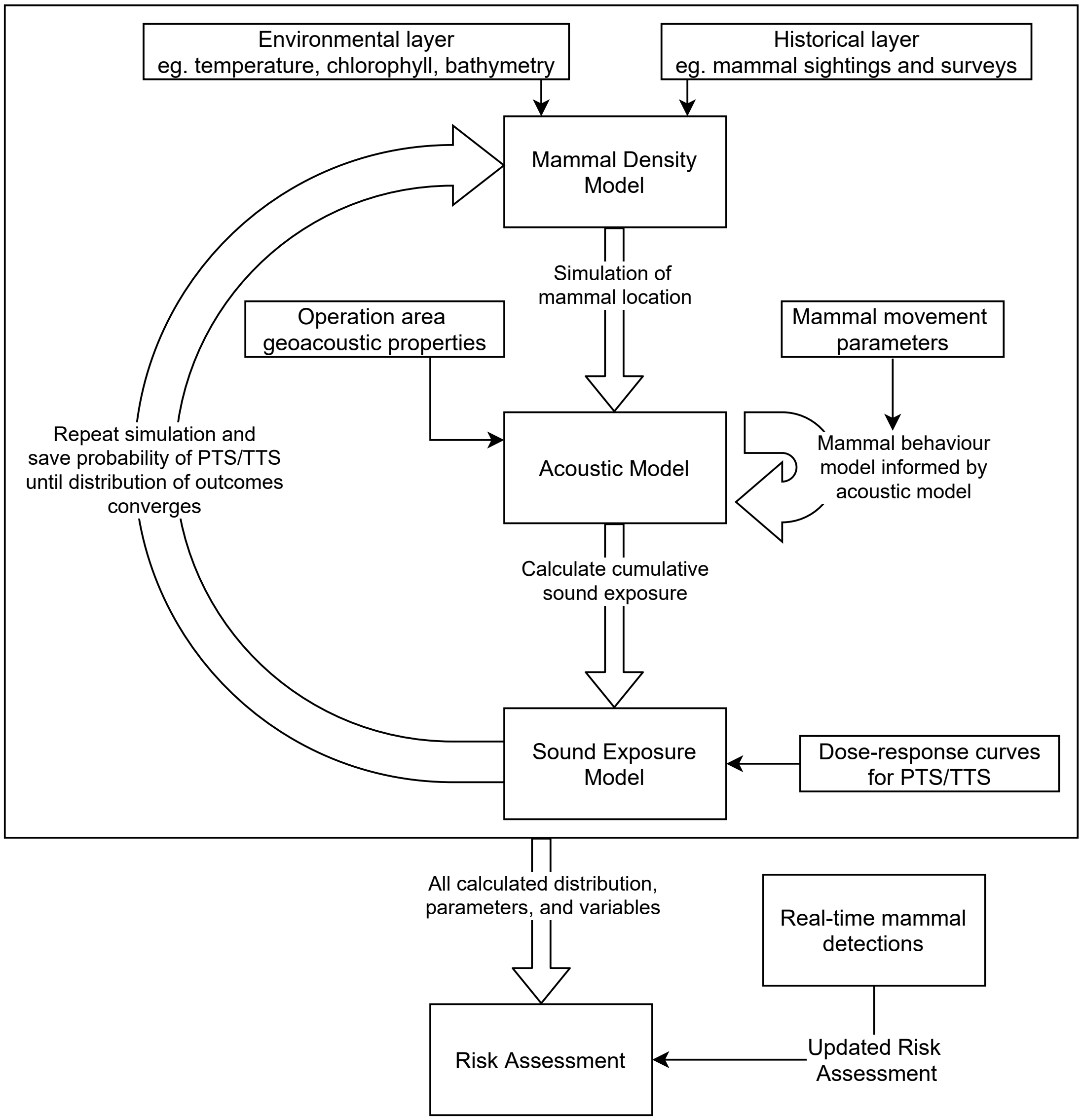

Figure 9: *Workflow of decision support tool. The models from Section 2 form a workbench for simulating marine mammals and their sound exposure. Everything from the workbench can then be fed into a risk assessment to form a decision support tool.*

The Log-Gaussian Cox process models provide the most promising framework for incorporating disparate sightings datasets together into a single mammal density model and acoustic models exist which can appropriately model the ensonified operation areas. However, dose-response curves do not presently exist for all species and thus TTS/PTS threshold values would have to be used. Future research efforts into understanding the behavioural responses to active sonar and converting that data into dose-response curves would provide better estimates of population proportions impacted by TTS/PTS onset in ensonified areas. Further development of PCoD models would also allow for incorporating long-term population impacts in the risk assessment.

The development of this workbench will provide the framework for a future decision support tool that incorporates real-time data in updated risk assessments. This support tool would allow the CAF to leverage historical and real-time data to reduce risk to marine mammals in combination with the use of existing mitigation procedures.

References

[1] Thomson, D. J. (2018), Recommendations for management of the effects of RCAF low frequency active sonar on marine mammals. Defence Research and Development Canada, Scientific Letter, DRDC-RDDC-2018-L18-0927-00836.

[2] Golder Associates Ltd. (2020), Evaluation of Acoustic Impacts and Mitigation Evaluation. Physical Activity: Deployment of AN/SSQ-565 Multistatic Low Frequency Active Source Sonobuoy and Helicopter Long Range Active Sonar (HELRAS DS-100) in MARPAC OPAREAS. Report No. 18106015-011-R-Rev0.

[3] Department of the Navy (2012), Final Supplemental Environmental Impact Statement/Supplemental Overseas Environmental Impact Statement For Surveillance Towed Array Sensor System Low Frequency Active (SURTASS LFA) Sonar. https://www.navfac.navy.mil/content/dam/navfac/Environmental/PDFs/NEPA/SURTASS_LFA_FSEIS-SOEIS.pdf, Last accessed on 2021-11-30.

[4] Department of National Defence, Interim Marine Mammal Risk Mitigation. Instructions For Use of LRP MSA And MH Sonar. 1267-1 (SSO ISR). Department of National Defence, Canada.

[5] von Benda-Beckmann, A. M., Wensveen, P. J., Kvadsheim, P. H., Lam, F.-P. A., Miller, P. J., Tyack, P. L., and Ainslie, M. A. (2016), Assessing the effectiveness of ramp-up during sonar operations using exposure models, In *The Effects of Noise on Aquatic Life II*, pp. 1197–1203, Springer.

[6] Watson, J., Joy, R., Tollit, D., Thornton, S. J., and Auger-Méthé, M. (2019), Estimating animal utilization distributions from multiple data types: a joint spatio-temporal point process framework, *arXiv preprint arXiv:1911.00151*.

[7] Buckland, S., Anderson, D., Burnham, K., and Laake, J. (1993), Distance sampling: estimating abundance of biological populations, *Chapman & Hall, London, United Kingdom*.

[8] Yuan, Y., Bachl, F. E., Lindgren, F., Borchers, D. L., Illian, J. B., Buckland, S. T., Rue, H., Gerrodette, T., et al. (2017), Point process models for spatio-temporal distance sampling data from a large-scale survey of blue whales, *The Annals of Applied Statistics*, 11(4), 2270–2297.

[9] Mannocci, L., Boustany, A. M., Roberts, J. J., Palacios, D. M., Dunn, D. C., Halpin, P. N., Viehman, S., Moxley, J., Cleary, J., Bailey, H., et al. (2017), Temporal resolutions in species distribution models of highly mobile marine animals: Recommendations for ecologists and managers, *Diversity and Distributions*, 23(10), 1098–1109.

[10] Roberts, J. J., Best, B. D., Mannocci, L., Fujioka, E., Halpin, P. N., Palka, D. L., Garrison, L. P., Mullin, K. D., Cole, T. V., Khan, C. B., et al. (2016), Habitat-based

cetacean density models for the US Atlantic and Gulf of Mexico, *Scientific reports*, 6(1), 1–12.

[11] Halpin, P. N., Read, A. J., Fujioka, E., Best, B. D., Donnelly, B., Hazen, L. J., Kot, C., Urian, K., LaBrecque, E., Dimatteo, A., et al. (2009), OBIS-SEAMAP: The world data center for marine mammal, sea bird, and sea turtle distributions, *Oceanography*, 22(2), 104–115.

[12] Kaschner, K., Watson, R., Trites, A., and Pauly, D. (2006), Mapping world-wide distributions of marine mammal species using a relative environmental suitability (RES) model, *Marine Ecology Progress Series*, 316, 285–310.

[13] Bradford, A. L., Forney, K. A., Oleson, E. M., and Barlow, J. (2017), Abundance estimates of cetaceans from a line-transect survey within the US Hawaiian Islands Exclusive Economic Zone., *Fishery Bulletin*, 115(2).

[14] National Marine Fisheries Service (NMFS) National Oceanic and Atmospheric Administration (NOAA), Commerce (2019), Takes of Marine Mammals Incidental to Specified Activities: Taking Marine Mammals Incidental to U.S. Navy Surveillance Towed Array Sensor System Low Frequency Active Sonar Training and Testing in the Central and Western North Pacific Ocean and Eastern Indian Ocean [Proposed rule; request for comments]. https://www.federalregister.gov/documents/2019/03/01/2019-03298/takes-of-marine-mammals-incidental-to-specified-activities-taking-marine-mammals-incidental-to-us#h-57, Last accessed on 2021-03-11.

[15] National Marine Fisheries Service (NMFS) National Oceanic and Atmospheric Administration (NOAA), Commerce (2019), Takes of Marine Mammals Incidental to Specified Activities: Taking Marine Mammals Incidental to U.S. Navy Surveillance Towed Array Sensor System Low Frequency Active Sonar Training and Testing in the Central and Western North Pacific Ocean and Eastern Indian Ocean [Final rule; notification of issuance of Letter of Authorization]. https://www.federalregister.gov/documents/2019/08/13/2019-16695/takes-of-marine-mammals-incidental-to-specified-activities-taking-marine-mammals-incidental-to-us, Last accessed on 2021-03-11.

[16] National Marine Fisheries Service (NMFS) National Oceanic and Atmospheric Administration (NOAA), Commerce (2020), Takes of Marine Mammals Incidental to Specified Activities; Taking Marine Mammals Incidental to U.S. Navy 2020 Ice Exercise Activities in the Beaufort Sea and Arctic Ocean [Notice; issuance of an Incidental Harassment Authorization (IHA)]. https://www.federalregister.gov/documents/2020/02/05/2020-02167/takes-of-marine-mammals-incidental-to-specified-activities-taking-marine-mammals-incidental-to-us, Last accessed on 2021-03-11.

[17] Costello, M., Stocks, K., Zhang, Y., Grassle, J., and Fautin, D. (2007), About the Ocean biogeographic information system, (Technical Report) Ocean Biogeographic Information System.

[18] Harvey, G. K., Nelson, T. A., Fox, C. H., and Paquet, P. C. (2017), Quantifying marine mammal hotspots in British Columbia, Canada, *Ecosphere*, 8(7), e01884.

[19] Efford, M., Buckland, L., et al. (2008), Advanced Distance Sampling. Estimating Abundance of Biological Populations, *Environmental Conservation*, 35(2), 187.

[20] Williams, R. and O'Hara, P. (2010), Modelling ship strike risk to fin, humpback and killer whales in British Columbia, Canada, *Journal of Cetacean Research and Management*, 11(1), 1–8.

[21] Nordlund, N., Benders, F., and Kvadsheim, P. H. (2011), SONATE 2011-a decision aid tool to mitigate the impact of sonar operations on marine life.

[22] Donovan, C. R., Harris, C. M., Milazzo, L., Harwood, J., Marshall, L., and Williams, R. (2017), A simulation approach to assessing environmental risk of sound exposure to marine mammals, *Ecology and evolution*, 7(7), 2101–2111.

[23] International Electrotechnical Commission and International Organization for Standardization (2020), Quantities and units - Part 8: Acoustics, *ISO/IEC 80000-8*.

[24] Harwood, J., King, S., Booth, C., Donovan, C., Schick, R. S., Thomas, L., and New, L. (2016), Understanding the population consequences of acoustic disturbance for marine mammals, In *The effects of noise on aquatic life II*, pp. 417–423, Springer.

[25] von Benda-Beckmann, A., Zwan, T., van Riet, M., Benders, F., Ainslie, M., and te Raa, L. (2012), SAKAMATA: managing the risk of sonar sound on marine mammals.

[26] Schippers, P. (1986), Description and Some Results of the Operational Propagation Loss Model ALMOST (= Acoustic Loss Model for Operational Studies and Tasks), In *Ocean Seismo-Acoustics*, pp. 159–168, Springer.

[27] Frankel, A. S., Ellison, W. T., and Buchanan, J. (2002), Application of the Acoustic Integration Model (AIM) to predict and minimize environmental impacts, In *OCEANS'02 MTS/IEEE*, Vol. 3, pp. 1438–1443, IEEE.

[28] Shyu, H.-J. and Hillson, R. (2006), A software workbench for estimating the effects of cumulative sound exposure in marine mammals, *IEEE Journal of Oceanic Engineering*, 31(1), 8–21.

[29] Houser, D. S. (2006), A method for modeling marine mammal movement and behavior for environmental impact assessment, *IEEE Journal of Oceanic Engineering*, 31(1), 76–81.

[30] University of St Andrews (2014), Mitigating environmental impacts of naval sonar. https://impact.ref.ac.uk/casestudies/CaseStudy.aspx?Id=35248#, Last accessed on 2021-03-29.

[31] Finneran, J. J., Carder, D. A., Schlundt, C. E., and Ridgway, S. H. (2005), Temporary threshold shift in bottlenose dolphins (Tursiops truncatus) exposed to mid-frequency tones, *The Journal of the Acoustical Society of America*, 118(4), 2696–2705.

[32] Kastak, D., Southall, B. L., Schusterman, R. J., and Kastak, C. R. (2005), Underwater temporary threshold shift in pinnipeds: Effects of noise level and duration, *The Journal of the Acoustical Society of America*, 118(5), 3154–3163.

[33] Southall, B. L., Bowles, A. E., Ellison, W. T., Finneran, J. J., Gentry, R. L., Greene Jr, C. R., Kastak, D., Ketten, D. R., Miller, J. H., Nachtigall, P. E., et al. (2008), Marine mammal noise-exposure criteria: initial scientific recommendations, *Bioacoustics*, 17(1-3), 273–275.

[34] Moretti, D., Thomas, L., Marques, T., Harwood, J., Dilley, A., Neales, B., Shaffer, J., McCarthy, E., New, L., Jarvis, S., et al. (2014), A risk function for behavioral disruption of Blainville's beaked whales (Mesoplodon densirostris) from mid-frequency active sonar, *PloS one*, 9(1), e85064.

[35] Williams, R., Erbe, C., Ashe, E., Beerman, A., and Smith, J. (2014), Severity of killer whale behavioral responses to ship noise: A dose–response study, *Marine pollution bulletin*, 79(1-2), 254–260.

[36] Miller, P. J., Antunes, R. N., Wensveen, P. J., Samarra, F. I., Catarina Alves, A., Tyack, P. L., Kvadsheim, P. H., Kleivane, L., Lam, F.-P. A., Ainslie, M. A., et al. (2014), Dose-response relationships for the onset of avoidance of sonar by free-ranging killer whales, *The Journal of the Acoustical Society of America*, 135(2), 975–993.

[37] Southall, B. L., Finneran, J. J., Reichmuth, C., Nachtigall, P. E., Ketten, D. R., Bowles, A. E., Ellison, W. T., Nowacek, D. P., and Tyack, P. L. (2019), Marine mammal noise exposure criteria: updated scientific recommendations for residual hearing effects., *Aquatic Mammals*, 45(2).

[38] Tyack, P. L. and Thomas, L. (2019), Using dose–response functions to improve calculations of the impact of anthropogenic noise, *Aquatic Conservation: Marine and Freshwater Ecosystems*, 29, 242–253.

[39] Atlantic Fleet Training and Testing (2017), Marine Resource Protection, [Fact Sheet]. https://media.defense.gov/2019/Mar/26/2002105649/-1/-1/1/4.%20AFTT%20EIS_OEIS%20-%20MARINE%20RESOURCE%20PROTECTION%20FACT%20SHEET%20-%20FINAL%20-%202017-05-10.PDF, Last accessed on 2021-03-09.

[40] Nissen, Jene (2012), Protective Measures Assessment Protocol (PMAP), [Fact Sheet]. https://pugetsoundblogs.com/waterways/files/2012/03/PMAP-sheet1.pdf, Last accessed on 2021-03-09.

[41] E&P Sound & Marine Life Programme, Development of transfer functions for the population consequences of acoustic disturnance model (PCAD). https://www.soundandmarinelife.org/innovation/development-of-transfer-functions-for-the-population-consequences-of-acoustic-disturbance-model-pcad.aspx, Last accessed on 2021-03-11.

[42] Consulting, S., Population Consequences of Disturbance. http://www.smruconsulting.com/products-tools/pcod/, Last accessed on 2021-03-11.

[43] GeoSolutions Group, NATO STO-CMRE IDA Decision Support System. https://www.geosolutionsgroup.com/portfolio/nato-sto-cmre-ida-decision-support-system, Last accessed on 2021-03-09.

[44] Weinberg, H. and Keenan, R. E. (1996), Gaussian ray bundles for modeling high-frequency propagation loss under shallow-water conditions, *The Journal of the Acoustical Society of America*, 100(3), 1421–1431.

[45] Keenan, R. and Gainey, L. (2015), US Navy Acoustic Effects Model (NAEMO) Acoustic Propagation Analysis Process Review Final Report.

[46] Li, D. X. (2000), On default correlation: A copula function approach, *The Journal of Fixed Income*, 9(4), 43–54.

[47] Artzner, P., Delbaen, F., Eber, J.-M., and Heath, D. (1999), Coherent measures of risk, *Mathematical finance*, 9(3), 203–228.

[48] Markowitz, H. (1952), Portfolio selection, *The Journal of Finance*, 7(1), 77–91.

[49] Föllmer, H. (2014), Spatial risk measures and their local specification: The locally law-invariant case, *Statistics & Risk Modeling*, 31(1), 79–101.

[50] Koch, E. (2017), Spatial risk measures and applications to max-stable processes, *Extremes*, 20(3), 635–670.

[51] Koch, E. (2019), Spatial risk measures and rate of spatial diversification, *Risks*, 7(2), 52.

[52] Nevat, I., Pignatta, G., Ruefenacht, L. A., and Acero, J. A. (2020), A decision support tool for climate-informed and socioeconomic urban design, *Environment, Development and Sustainability*, pp. 1–25.

[53] Taleb, N. N. (2007), The black swan: The impact of the highly improbable, Vol. 2, Random house.

[54] Marques, T. A., Thomas, L., Martin, S. W., Mellinger, D. K., Ward, J. A., Moretti, D. J., Harris, D., and Tyack, P. L. (2013), Estimating animal population density using passive acoustics, *Biological Reviews*, 88(2), 287–309.

[55] Jakobsson, M., Mayer, L., Coakley, B., Dowdeswell, J. A., Forbes, S., Fridman, B., Hodnesdal, H., Noormets, R., Pedersen, R., Rebesco, M., et al. (2012), The international bathymetric chart of the Arctic Ocean (IBCAO) version 3.0, *Geophysical Research Letters*, 39(12).

[56] Mäkinen, J. and Vanhatalo, J. (2016), Hydrographic responses to regional covariates across the Kara Sea, *Journal of Geophysical Research: Oceans*, 121(12), 8872–8887.

[57] Cavalieri, D., Parkinson, C., Gloersen, P., and Zwally, H. (1996), updated yearly. Sea Ice Concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS Passive Microwave Data, Version 1, Boulder, Colorado USA, NASA National Snow and Ice Data Center Distributed Active Archive Center.

[58] Mäkinen, J. and Vanhatalo, J. (2018), Hierarchical Bayesian model reveals the distributional shifts of Arctic marine mammals, *Diversity and Distributions*, 24(10), 1381–1394.

[59] Simons, R. (2020), ERDDAP. https://coastwatch.pfeg.noaa.gov/erddap, Last accessed on 2021-03-22. Monterey, CA: NOAA/NMFS/SWFSC/ERD.

[60] NOAA National Geophysical Data Center (2006), 2-minute gridded global relief data (ETOPO2) v2. https://doi.org/10.7289/V5J1012Q, Last accessed on 2021-03-22.

[61] Levitus, S. (2012), NODC Standard Product: World Ocean Atlas 1998 (National Oceanographic Data Center 7 disc set) (NCEI Accession 0095184). NOAA National Centers for Environmental Information. Dataset. https://accession.nodc.noaa.gov/0095184, Last accessed on 2021-03-22.

List of Symbols/Abbreviations/Acronyms/Initialisms

AIM	Acoustic Integration Model
ALMOST	Acoustic Loss Model for Operational Studies and Tasks
CAF	Canadian Armed Forces
CASS/GRAB	Comprehensive Acoustic Simulation System/Gaussian Ray Bundle
CVaR	conditional value at risk
DCS	directed client support
DFO	Department of Fisheries and Oceans
EAD	exposure at default
ERMC	Environmental Risk Management Capability
ES	expected shortfall
ESME	Effects of Sound on the Marine Environment
GIS	geographic information system
IDA	Integrated Decision Aide
LFAS	low frequency active sonar
LGD	loss given default
MARLANT SE	Maritime Forces Atlantic Safety and Environment
MARPAC SE	Maritime Forces Pacific Safety and Environment
MAZ	mitigation avoidance zone
NAEMO	Navy Acoustic Effects Model
NATO	North Atlantic Treaty Organization
NL	Netherlands
NRL	Naval Research Laboratory
OBIS	Ocean Biodiversity Information System
ONR	Office of Naval Research
PCAD	Population Consequences of Acoustic Disturbance
PCoD	Population Consequences of Disturbance

PMAP	Protective Measures Assessment Protocol
PTS	permanent threshold shift
RCAF	Royal Canadian Air Force
SAFESIMM	Statistical Algorithms for Estimating the Sonar Influence on Marine Megafauna
SAKAMATA	Sea Animal Kind Area-dependant Mitigated Active Transmission Aid
SARA	Species at Risk Act
SEAMAP	Spatial Ecological Analysis of Megavertebrate Populations
SEL	sound exposure level
SPL	sound pressure level
3 MB	Marine Mammal Movement and Behaviour
TTS	temporary threshold shift
UK	United Kingdom
UKHO	United Kingdom Hydrographic Office
US	United States
VaR	value at risk

DOCUMENT CONTROL DATA

*Security markings for the title, abstract and keywords must be entered when the document is sensitive.

1. ORIGINATOR (The name and address of the organization preparing the document. A DRDC Centre sponsoring a contractor's report, or a tasking agency, is entered in Section 8.) DRDC – Atlantic Research Centre PO Box 1012, Dartmouth NS B2Y 3Z7, Canada	2a. SECURITY MARKING (Overall security marking of the document, including supplemental markings if applicable.) CAN UNCLASSIFIED 2b. CONTROLLED GOODS NON-CONTROLLED GOODS DMC A

3. TITLE (The document title and subtitle as indicated on the title page.)

A multidisciplinary approach for mitigating the risk of harm to marine mammals from sound exposure

4. AUTHORS (Last name, followed by initials – ranks, titles, etc. not to be used. Use semi-colon as delimiter.)

Day, A. C.

5. DATE OF PUBLICATION (Month and year of publication of document.)	6a. NO. OF PAGES (Total pages, including Annexes, excluding DCD, covering and verso pages.)	6b. NO. OF REFS (Total cited in document.)
February 2022	44	61

7. DOCUMENT CATEGORY (e.g., Scientific Report, Contract Report, Scientific Letter)

Scientific Report

8. SPONSORING CENTRE (The name and address of the department project or laboratory sponsoring the research and development.)

DRDC – Atlantic Research CentrePO Box 1012, Dartmouth NS B2Y 3Z7, CanadaPO Box 1012, Dartmouth NS B2Y 3Z7, Canada

9a. PROJECT OR GRANT NO. (If appropriate, the applicable research and development project or grant number under which the document was written. Please specify whether project or grant.)	9b. CONTRACT NO. (If appropriate, the applicable contract number under which the document was written.)
01dz	

10a. DRDC PUBLICATION NUMBER	10b. OTHER DOCUMENT NO(s). (Any other numbers which may be assigned to this document either by the originator or by the sponsor.)
DRDC-RDDC-2022-R032	

11a. FUTURE DISTRIBUTION WITHIN CANADA (Approval for further dissemination of the document. Security classification must also be considered.)

Public release

11b. FUTURE DISTRIBUTION OUTSIDE CANADA (Approval for further dissemination of the document. Security classification must also be considered.)

Public release

12. KEYWORDS, DESCRIPTORS or IDENTIFIERS (Use semi-colon as a delimiter.)

marine mammals; agent based modelling; risk modelling; risk; noise exposure

13. ABSTRACT/RÉSUMÉ (When available in the document, the French version of the abstract must be included here.)

This Scientific Report reviews the models that make up existing decision support tools for mitigating the risk of sonar exposure to marine mammals. The models include: a density model to simulate the location of marine mammals, an acoustic model to determine sound propagation, an exposure model to determine the total sound exposure and impact to a simulated mammal, and behaviour models that allow the simulated mammal to move through the sound field. Although the challenges are considerable, understanding the workflow of the various models and the importance of the data is key. Joining the models into a system or workbench, does progress the work towards a mitigation tool. However, incorporating defined risk assessment measures that address mammal-specific requirements is a critical component.

Using aspects of financial risk management, examples of risk measures that may be applicable to quantifying risk of harm to marine mammals due to sound exposure are described. In addition, the complexity of risk and of combining these models into a single tool for marine mammal risk mitigation is highlighted. A deficiency in data and issues associated with real-time data assimilation into many of the models are also indicated.

Ce rapport passe en revue les modèles qui composent les outils d'aide à la décision existants pour atténuer le risque d'exposition des sonars aux mammifères marins. Les modèles comprennent : un modèle de densité pour simuler l'emplacement des mammifères marins, un modèle acoustique pour déterminer la propagation du son, un modèle d'exposition pour déterminer l'exposition sonore totale et l'impact sur un mammifère simulé, et des modèles de comportement qui permettent au mammifère simulé de se déplacer à travers le champ sonore. Bien que les défis soient considérables, comprendre le workflow des différents modèles et l'importance des données est essentiel. L'intégration des modèles dans un système ou un plan de travail fait progresser le travail vers un outil d'atténuation. Cependant, l'incorporation de mesures d'évaluation des risques définies qui répondent aux exigences spécifiques aux mammifères est un élément essentiel.

À l'aide d'aspects de la gestion des risques financiers, des exemples de mesures de risque qui peuvent être applicables à la quantification du risque de dommages aux mammifères marins en raison d'une exposition sonore sont décrits. De plus, la complexité du risque et de la combinaison de ces modèles en un seul outil d'atténuation des risques pour les mammifères marins est soulignée. Un manque de données et des problèmes associés à l'assimilation de données en temps réel dans de nombreux modèles sont également indiqués.