

ERA Acute Report

WP2a. Sensitivity and Uncertainty testing

ERA Acute Report	
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	Number of pages: 99
	Document ID: ERA Acute 2A-2
Summary: This report is part of ERA Acute DEMO2000 JIP. This document provides the results for Work Package 2a: Uncertainty and sensitivity analyses for the surface compartment, the surface- shoreline- and the water column compartments. The analyses have been performed using a deterministic and a stochastic approach.	
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Terms and definitions

Term	Definition and description
Parameter	A term in the model that must be supplied as input for a model to be able to generate output. Its value is fixed during a model run
Model	A set of mathematical equations that attempts to describe a system (physical, biological, economic, or social)
Monotonic	A relationship or function which preserves a given trend, i.e. the relationship between two factors does not change direction
Output, endpoint, result	Data generated by the model based on the input parameters
Variable	Same as parameter, but its value change during a model run
Harmful oil	General expression used to indicate oil which may be lethal for VECs. It may be oil film thickness above a certain thickness threshold, oil mass above a certain mass threshold, total oil concentration above a certain concentration level etc.

1 Introduction

The study described herein is part of ERA Acute DEMO2000 JIP. The report presents the results for Work Package 2a: Uncertainty and sensitivity analyses for the surface compartment, the shoreline compartment and the water column compartment. An overview of the Work Package's place in the ERA Acute project is illustrated in Figure 1.

A mathematical model approximates something in the real world. Every model has some inherent uncertainty. To gain understanding of a model's precision, three steps are necessary

- Model verification (check that the model calculates the algorithms correctly and meets specification) (WP1a) and that it delivers the necessary results (WP1b)
- Model sensitivity (analyse the effects of lack of knowledge and model's response to changes in model input and parameters) (WP2a)
- Model validation (decide on the conformity/consistency between model results and observations and with other models) (WP2b and WP2c)

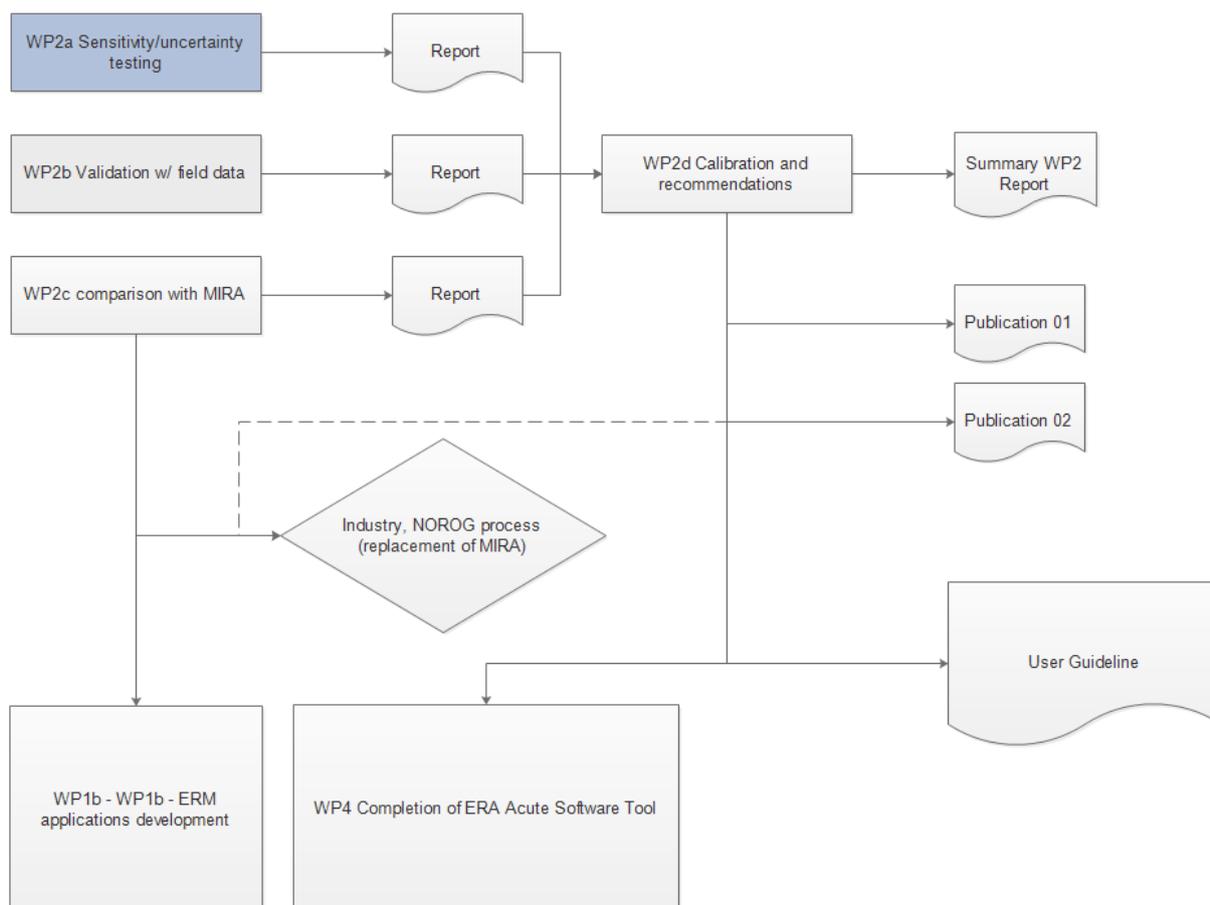


Figure 1. A schematic overview of the different work packages in WP2 with selected output and inter-dependent activities.

A test protocol for the uncertainty and sensitivity analyses of the ERA acute methodology has been derived (Bjørgesæter et al., 2016). The protocol introduces the analyses, describes the tools and methods to be used in analyses, and gives a description of the compartment specific tests to be performed.

The protocol is divided into the following eight major steps (see Bjørgesæter et al., 2016 for details):

1. Specify endpoints.
2. Define input parameters.
3. Determine and account for correlations among parameters.
4. Generate samples as input to the ERA Acute models developed in Phase 3 of ERA Acute project.
5. Run the ERA Acute models developed in Phase 3 of ERA Acute project.
6. Perform uncertainty analysis: Derive quantitative statements of uncertainty in terms of a subjective confidence interval for the unknown value.
7. Perform sensitivity analysis: Rank the parameters contributing most to uncertainty in the model prediction by performing a sensitivity analysis.
8. Present and interpret the results of the analysis.

The reader is referred to the test protocol for a detailed description and examples of the different steps.

1 Methods

Uncertainty and sensitivity analysis are two techniques for evaluating models. Although both techniques are often mixed together, they each have a different purpose.

- **Uncertainty Analysis** – Investigates the effects of lack of knowledge or potential errors of the model (e.g. the uncertainty associated with parameter values or model design and output) (Gaber et al., 2009).
- **Sensitivity Analysis** - The computation of the effect of changes in input values or assumptions (including boundaries and model functional form) on the outputs (Gaber et al., 2009).

When conducted in combination, sensitivity and uncertainty analysis allow model users to be more informed about the confidence that can be placed in model results (Gaber et al., 2009). A model's quality to support a decision becomes better known when information is available to assess these factors.

Two main approaches to the analyses are used in this report:

- (1) deterministic
- (2) stochastic

Deterministic: Deterministic sensitivity analyses describe how the model output changes based on changing the value of one input parameter at a time. Maximum (worst), minimum (best) and most likely estimates, or a percentage value of change (+/-) from a defined base value of an input parameter are typically used. The interpretation of the results is relatively straightforward. Small changes in the model output value indicates that the output is robust (i.e. not very sensitive) to changes in parameter values within the model. If, on the other hand, the value of the model output changes markedly when we change some parameters in the model within their reasonable range, this indicates that the model output is sensitive to changes in parameter values (Uusitalo et al., 2015).

The advantage of the deterministic approach is that it requires few simulations and is thus valuable for examining models that may become costly in terms of computer time (e.g. testing oil drifts statistics used in the models).

The disadvantages of the deterministic approach include that only a few discrete outcomes are considered, it gives equal weight to each outcome, and possible interdependence between inputs are difficult to identify and quantify. Assessing the likelihood of different outcomes is thus not possible, and it is difficult to identify and rank the input parameter in terms of importance on the model output.

Stochastic: All models in the ERA Acute project are deterministic. The simplest way to make a deterministic model stochastic is to use repeated random sampling (Monte Carlo methods), in which configurations of model inputs are drawn randomly from their distribution, and the resulting set of model outputs can be seen as a random sample of the distribution of the output of interest (Helton et al., 2006).

An illustration of the technique is presented in Figure 2. The figure shows the probability distributions of three input parameters (x_1 , x_2 , and x_3). Instead of changing the input parameters one value at a time, they are assigned a probability distribution. The Monte Carlo simulation is performed by drawing a value at random from each probability distribution and then computing the result. The process is repeated several times, each time using a different set of random values from the probability distributions. The number of runs that will be performed depends on the results from the uncertainty analysis and may range from three to several thousand.

The result is a matrix with n values for each input parameter with corresponding values for the model output (model predictions, results or endpoint). This matrix is the input to the uncertainty and sensitivity analysis.

The uncertainty and sensitivity analysis are performed directly on the matrix.

The uncertainty analysis is performed by using a standard set of descriptive statistics, e.g. the most likely outcome, the likelihood for outcome above a specific value etc. An illustration is presented in Figure 2, showing how the model output Y varies due to the uncertainty in the model input values as a histogram together with some selected statistics. Using $P_{2.5}$ and $P_{97.5}$ as lower and upper percentile yields what is referred to as a *subjective* 95% confidence interval, where subjective indicates that the interval is calculated from repeated sampling and not from real measurements.

The sensitivity analysis is performed using the Sampling and Sensitivity Analysis Tool for Computational Modelling (SaSat) (Hoare et al., 2008a, 2008b). The sensitivity analysis is performed by Pearson and Spearman correlation coefficient, Partial Rank Correlation Coefficient (PRCC) analysis and Factor Prioritization by Reduction of Variance. Combined the methods can rank and quantify the most important input parameters.

PRCC can be used to determine the statistical relationships between each input parameter and each output result while keeping all the other input parameters constant at their expected value. This allows independent effects of each parameter to be determined, even when the parameters are correlated. The interpretation of PRCCs assumes a monotonic relationship (relationship or function which preserves a given trend) between parameters (which are the case for all the models used in ERA Acute). The rank-transformation is done to reduce the effect of non-linear data, and PRCC is a robust sensitivity measure for nonlinear relationships.

Factor prioritization is a broad term denoting a group of statistical methodologies for ranking the importance of parameters contributing to the model output. The objective of reduction of variance is to identify the parameter which would lead to the greatest reduction in the variance of the model output parameter of interest. The second most important parameter is then determined etc., until all independent input parameters are ranked. The results are given as a Sensitivity index (S_i) which is a value between 0 and 1. A high value of S_i implies that the model input parameter is an important parameter. The value of the sensitivity index is the proportion of the total variance attributable to the given input parameter.

An illustration of the results from the factor prioritization by reduction of variance analysis is shown in Figure 2. The sensitivity index represents the amount of variability in the model output that is attributable to each input parameter. The results show that the model output Y is most sensitive to input parameter X_3 and least sensitive to the X_1 parameter, and that the input parameter X_3 accounts for 61% of the variability in the model output Y . Thus, in contrast to the deterministic analysis which gives equal weight to each outcome, a stochastic analysis can rank the importance of the input parameters and give a quantitative number of the importance of each parameter.

Stochastic uncertainty and sensitivity analyses involves defining and generating sample values for the model input data and the model output data (model predictions, results or endpoints). Defining the model input data values includes setting a range of possible values (minimum and maximum) and a probability distribution. Selecting a suitable range and distribution of the model parameters requires knowledge about the input data in the model and properties to different statistical distributions (cf. Bjørgesæter et al., 2016 for the most relevant distributions for the input parameters in ERA Acute models and their properties).

A decision tree diagram for choosing a distribution is illustrated in Figure 3 (Damodaran, 2007). In this report various goodness of fit tests, primarily Akaike information criterion, Anderson–Darling test and Kolmogorov–Smirnov test was used to find the appropriate probability distribution from modelled data when possible.

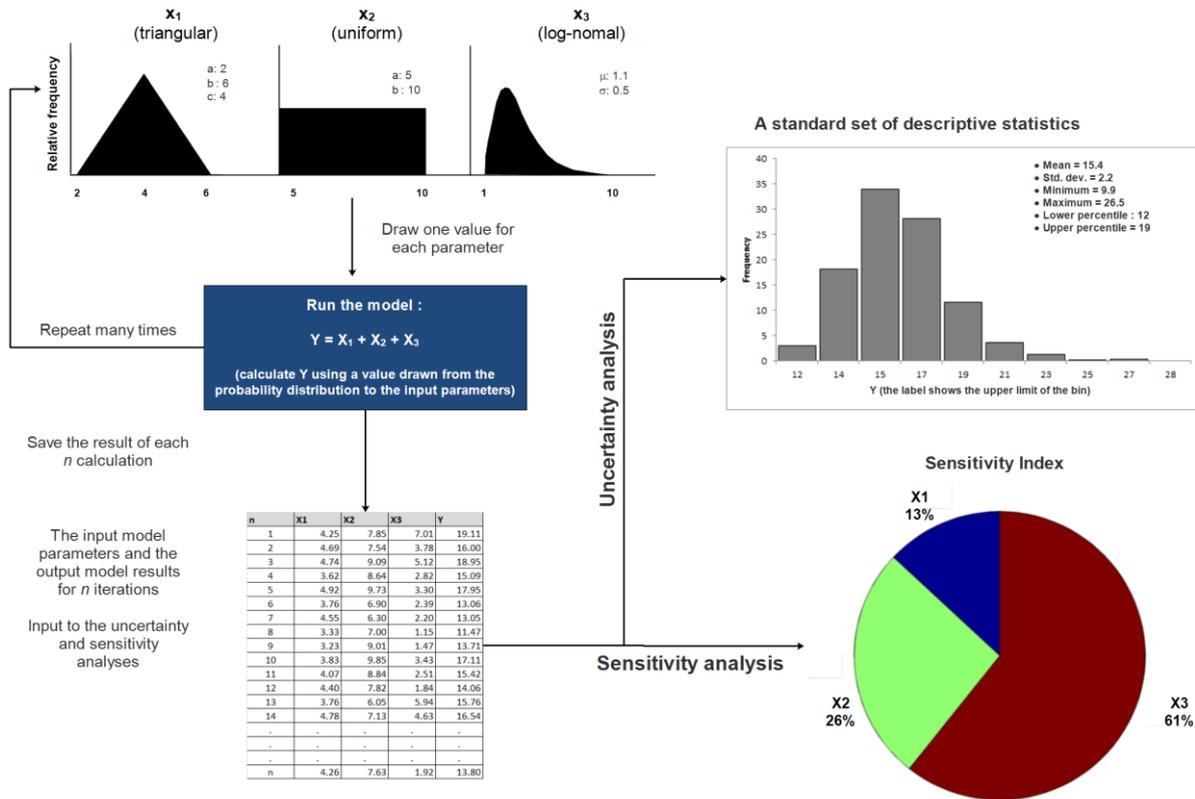


Figure 2. Illustration of stochastic uncertainty and sensitivity analyses. The ERA Acute model calculations are performed in the blue box. The uncertainty analyses are performed in Excel and sensitivity analyses are performed with the MATLAB toolbox sampling and sensitivity analysis tool for computational modelling (SaSAT)-

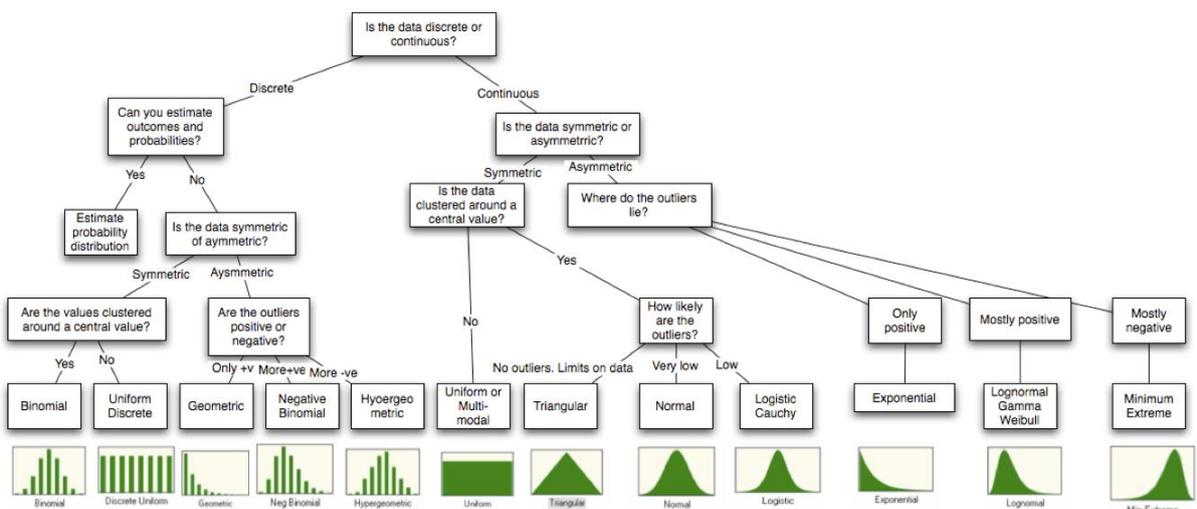


Figure 3. A decision tree diagram for choosing a distribution. Figure 6A.15 from [Probabilistic approaches to risk](#) by Damodaran (2007).

The surface compartment

This section is concerned with the sensitivity and uncertainty testing of the surface compartment model of ERA Acute. An overview of the different tests performed is presented in Table 1.

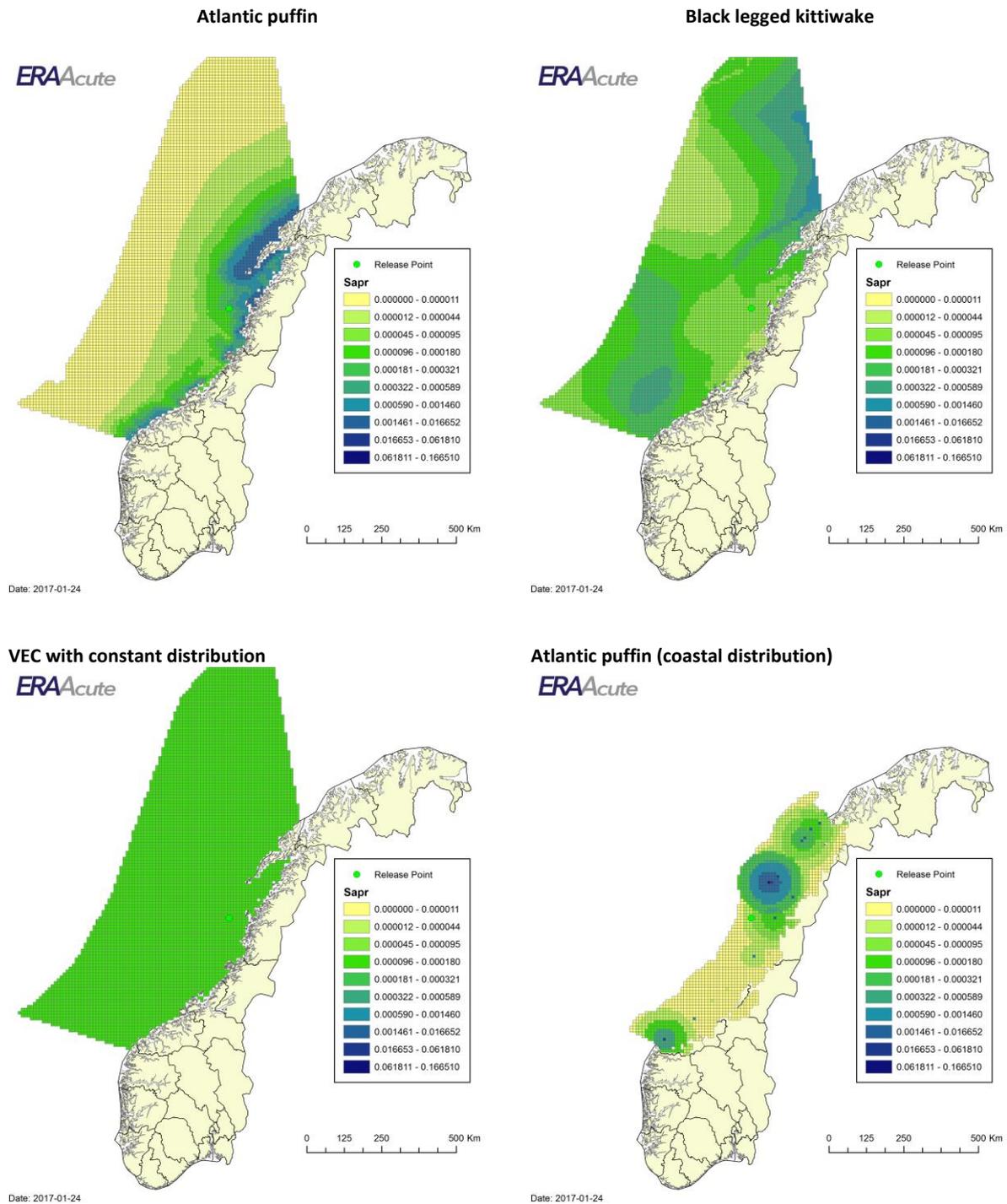
Table 1. Overview of test for the surface compartment (see text for more details).

Model	Parameter	Description	Endpoint
Impact models	Probability of mortality given contact with oil above a threshold (P_{beh})	Investigates the importance and sensitivity of the input parameters derived in Phase3. How important are uncertainty and variation in these parameters compared to typical variation in oil drift statistics and variability in different VEC datasets?	Impact
	Probability of encounter the sea surface (p_{phy})		
	Coverage (Cov)		
	Number or fraction of VEC in a grid cell (N)		
Oil drift parameters	Threshold thickness (TH)	Investigate the effect of using different threshold values for lethal film thickness (pre-and post) by running oil drift simulations.	Number, area and exposure time of harmful grid cells, impact
	Exposure time (T_{exp})	Perform a test designed to compare the results of the two equations. Which model gives best predictions compared to field data?	Impact
Population model	R	Investigate the importance and sensitivity of the input parameters derived in Phase3. Compare the population model with MIRA damage keys	Restitution and Recovery Damage Factor
	TLR		
	b		

The surface compartment is comprised of seabirds, marine mammals and sea turtles. The resource unit (N) is a population, which is characterised by (1) population density, (2) population distribution and (3) population size. The VECs are classified into two different kinds of wildlife groups according to their *individual vulnerability* and *population vulnerability*:

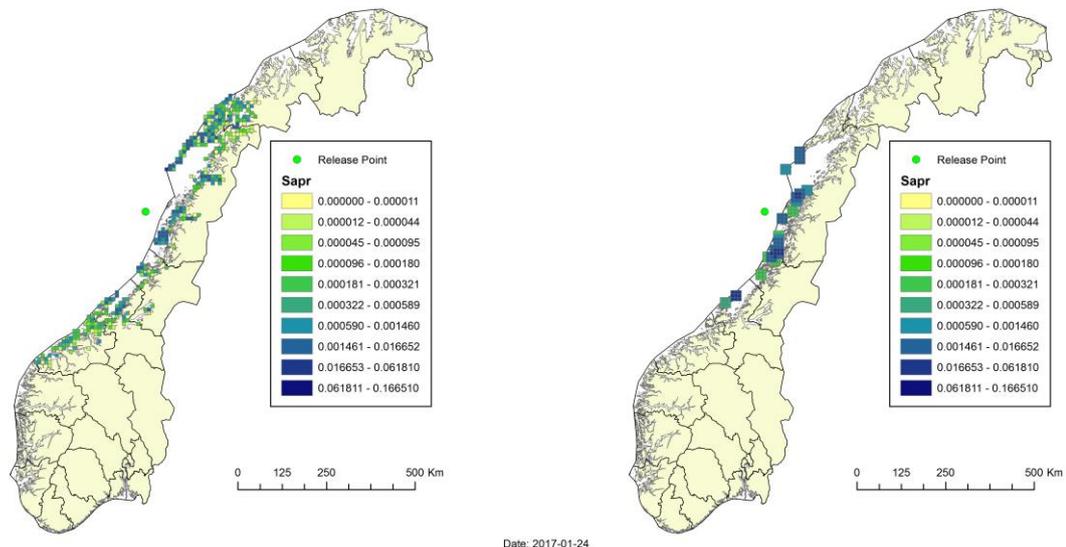
- individual vulnerability refers to a species physiological and toxicological sensitivity, and behavioural factors affecting the probability of fouling
- population vulnerability refers to vital life history parameters, such as fecundity and survival, affecting the potential rate of growth and long-term population size.

Six VECs with variable distributions in the Norwegian Sea are used in the analyses of the surface compartment. Three VECs with a wide spread distribution in the analysis area and three datasets with a more coastal distribution. The distribution of the VECs for one single month is illustrated in Figure 4.



Common eider
ERA Acute

Grey seal
ERA Acute



Date: 2017-01-24
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Figure 4. Illustration of the distribution and relative abundance of VECs used in the tests for the surface compartment.

Oil drift parameters (statistics) for the tests are derived from stochastic oil drift simulations using OSCAR v.8.1 (SINTEF, 2016) in combination with the Python script *pysemble*, satellite data from the Deepwater Horizon Oil Spill as well as defined probability distributions. A description off the setup of the oil drift model and the datasets are described in detail together with the corresponding test(s).

2 The impact models

The following two impact equations was constructed for the surface compartment in Phase 3 of the ERA Acute project (cf. Bjørgesæter and Damsgaard Jensen, 2015); one without (Eq. 2.1) and one with (Eq. 2.2) the oil drift statistics exposure time (T_{exp}).

$$N_{let-1} = \sum_{i=1}^n p_{beh} \times Cov_{iT} \times p_{phyT} \times N_i \quad 2.1$$

$$N_{let-2} = \sum_{i=1}^n N_i - (1 - p_{beh} \times Cov_{iT} \times p_{phyT})^{T_{expiT}} \times N_i \quad 2.2$$

Where N_{let-1} and N_{let-2} is the acute mortality, p_{beh} is the probability of encountering the sea surface and p_{phy} is the conditional probability of mortality given encounter with oil above an oil film thickness (T). Cov is the coverage of the grid cell i with harmful oil (i.e. the fraction of the cell covered with oil above T), T_{exp} is the exposure time of harmful oil in grid cell i with harmful oil (i.e. the period of cell is covered with oil above T) and N is the number of individuals or population fraction in grid cell i .

Test 1: In Phase 3, the p_{let} factor was divided into a behavioural (p_{beh}) and physiological (p_{phy}) and toxicological factor ($p_{let} = p_{beh} \times p_{phy}$) making the behavioural and physiological and toxicological vulnerability towards oil spills independent of each other (cf. Bjørgesæter and Damsgaard Jensen, 2015 for more details). A generic look-up table for 13 wildlife groups was constructed for each new factor based on species specific values derived from various published oil vulnerability indexes (Table 2).

Both factors are reported with three values (“least”, “intermediate” and “most” conservative). Investigating and analysing the importance and sensitivity of these factors will give insight into the importance of providing species specific values versus generic values for wildlife groups and identify the relative importance of the two factors compared to e.g. typical variation in oil drift statistics and natural variability in different VEC datasets.

Table 2. Individual vulnerability factors (p_{beh} and p_{phy}) derived in Phase 3.

NO	Wildlife groups	p_{beh}			p_{phy}			$p_{beh} \times p_{phy}$		
		LO	IM	HI	LO	IM	HI	LO	IM	HI
1	Pelagic diving seabirds	79%	79%	89%	80%	90%	100%	63%	71%	89%
2	Pelagic surface foraging seabirds	45%	45%	51%	80%	90%	100%	36%	41%	51%
3	Coastal diving seabirds	67%	67%	76%	80%	90%	100%	54%	61%	76%
4	Coastal surface feeding seabirds	31%	33%	44%	69%	78%	87%	21%	24%	33%
5	Wetland surface feeding seabirds	48%	48%	54%	80%	90%	100%	38%	43%	54%
6	Wading seabirds	35%	35%	35%	80%	90%	100%	28%	32%	35%
7	Baleen whales	35%	53%	88%	0.4%	0.4%	0.4%	0.2%	0.2%	0.4%
8	Toothed whales	40%	60%	100%	0.8%	0.8%	0.8%	0.3%	0.5%	0.8%
9	True seals, walrus and sea lions	83%	90%	96%	0.4%	2.8%	5.8%	0.4%	2.6%	5.7%
10	Fur seals	63%	78%	93%	50%	72%	93%	33%	57%	87%
11	Sea cows	95%	98%	100%	0.8%	4.3%	8.3%	0.8%	4.2%	8.3%
12	Aquatic mammals	79%	88%	97%	50%	72%	93%	40%	63%	90%
13	Sea turtles	95%	99%	100%	3.0%	3.0%	3.0%	2.9%	2.9%	3.0%

2.1 Uncertainty and sensitivity analysis

The base values and the probability distributions of the model input data used in the deterministic and stochastic uncertainty and sensitivity analyses are presented in Table 3. The base values used in the deterministic analyses are chosen so that the investigated range ($\pm 100\%$) cover the possible range of the input data values, except the exposure time. The exposure time is set to 15 days to investigate its effect over a range from 0 to 30 days.

For the stochastic analyses the uncertainty in the input data parameter is represented by a probability distribution (cf. Figure 3 in Chapter 1). The two individual behaviour factors are assigned a triangular distribution with mode (most likely value) equal to the intermediate estimate from Phase 3 (IM in Table 2) with a minimum and maximum value equal to the intermediate estimate \pm 25%. The probability distribution for oil drift parameters and resource dataset is based on different goodness of fit tests (see Chapter 1) from stochastic oil drift simulations performed in OSCAR and satellite data for Deepwater Horizon oil spill.

Table 3. Model table for the impact equation for the surface compartment. The endpoint (model output) for the analyses is acute mortality (N_{let-1} and N_{let-2}).

Input data	Base value	Parameters			Distribution
		Parameter 1	Parameter 2	Parameter 3	
P_{beh}	0.5	31%	76%	100%	Triangular
P_{phy}	0.5	0.4%	72%	100%	Triangular
Texp (days)	15	5	8		Log-normal
Coverage	0.5	0.10%	0.11%	100%	Triangular
N	0.5	1			Fixed

2.1.1 Deterministic sensitivity analysis

The analyses are carried out by varying one parameter at a time from a base (nominal) value and investigating the effect on the model output, while the other model input data are held constant at their base value (cf. Table 3). The most important input parameters are identified by the slope and the vertical width of the curves.

General pattern for all wildlife groups

Equation 3.1: N_{let-1} is the product of four model input parameters, and thus the model output N_{let-1} is initially equal sensitive to all four model input parameters. This is illustrated in Figure 5, showing how the value of the model output (N_{let-1}) changes as the sampled model input data values changes from their base value, either as percentage (Figure 5, top) or as absolute values, i.e. acute mortality (Figure 5, bottom). Since the base value for all parameters is 50%, N_{let-1} at $x = 0$, is equal to $0.5 (P_{beh}) \times 0.5 (Coverage) \times 0.5 (P_{phy}) \times 0.5 (N)$, or 6.25%. An increase of e.g. 40% from the base value in one model input parameter will result in a 40% increase in N_{let-1} (e.g. at $P_{beh} = 0.7$, $N_{let-1} = 0.7 \times 0.5 \times 0.5 \times 0.5$, or 8.75%, i.e. a 40% increase from 6.25%).

This is the property of a linear function, $y=ax+b$. The slope (a) gives the mortality rate and will vary according to the sensitivity of the VECs. A VEC that is vulnerable for oil on the sea surface (i.e. high P_{beh} and P_{phy}) such as an auk will have a steeper slope than a VEC that is defined as less vulnerable for oil on the sea surface (i.e. low P_{beh} and/or low P_{phy}) such as a baleen whale (cf. Table 2). Illustrations of how acute mortality estimated with equation 2.1 varies with different values for coverage and N for the different wildlife groups are presented in Figure 7 – Figure 19.

Equation 3.2: N_{let-2} is the product of the same four model input parameters but it also includes an exponentiation of the exposure time. The base value for this input parameter is set to 15 days (i.e. the exposure time varies from 0 to 30 days within the range shown). The effect of changing the input model parameters on N_{let-2} is illustrated in Figure 6. The curve of N is linear, and its curve diverges from the other parameters. At the model input parameters base values, N_{let-2} is 43%, i.e. considerably higher than N_{let-1} . The estimated mortality for the model input parameters and coverage increase more rapidly before they level of at an asymptote equal to their base values (i.e. 50%).

This is the property of an exponential function given by $y=a(1-e^{-bx})$. The mortality rate (b) of the function varies according to the sensitivity of the VECs. A VEC that is vulnerable for oil on the sea surface (i.e. high P_{beh} and P_{phy}) such as an auk will have a steeper slope than a VEC that is defined as less vulnerable for oil on the sea surface (i.e. low P_{beh} and/or low P_{phy}) such as a baleen whale (cf. Table 2). Illustrations of how acute mortality estimated with equation 2.1 varies with different values for coverage and N for the different wildlife groups are presented in Figure 7 – Figure 19.

N is the overall most important input parameter (largest width) but the relative importance of the parameters varies throughout the range tested. The oil drift statistics and the individual behaviour factors are more important than N for values smaller than the base values and less important than N for values higher than the base values. The reason why the curves diverge is because the Coverage, Texp, P_{beh} and P_{phy} relate to a base value of 0.5 for N, while N relates to a value of 0.5 and 15 days for Texp. Thus, increasing values of Coverage, Texp, P_{beh} and P_{phy} will converge at 0.5 (= 100% relative loss) while N will converge at 0.87 within the selected range.

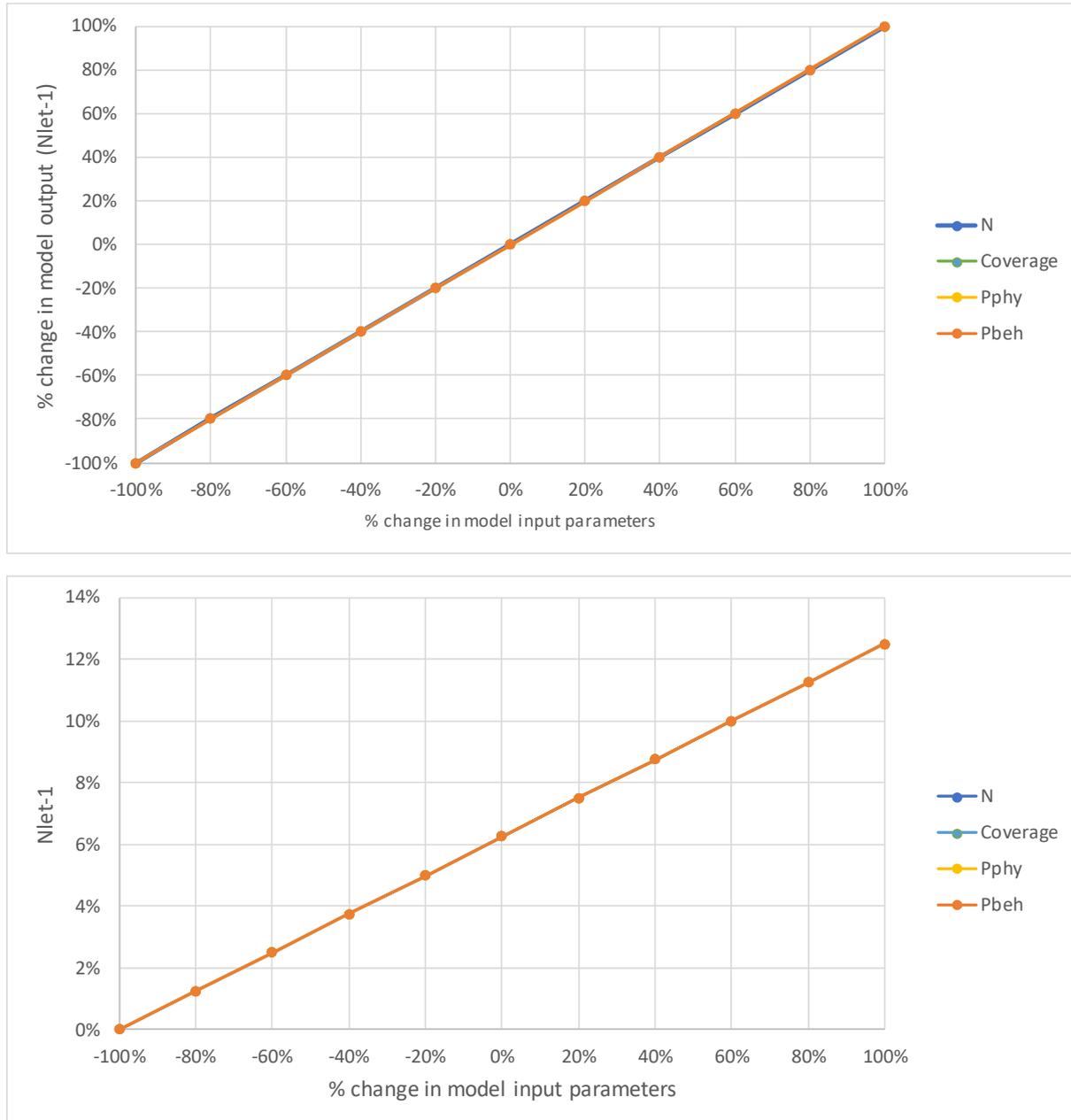


Figure 5. A spider graph comparing the effects of the individual vulnerability factors, the oil drift statistic coverage and the resource abundance model on the model output results (N_{let-1}). For each input the percentage changes in its value for the base case is plotted on the x-axis and the percentage (top) and absolute (bottom) change in results is plotted on the y-axis. Since all model input have identical impact on the model output all the graphs are plotted on top of each other.

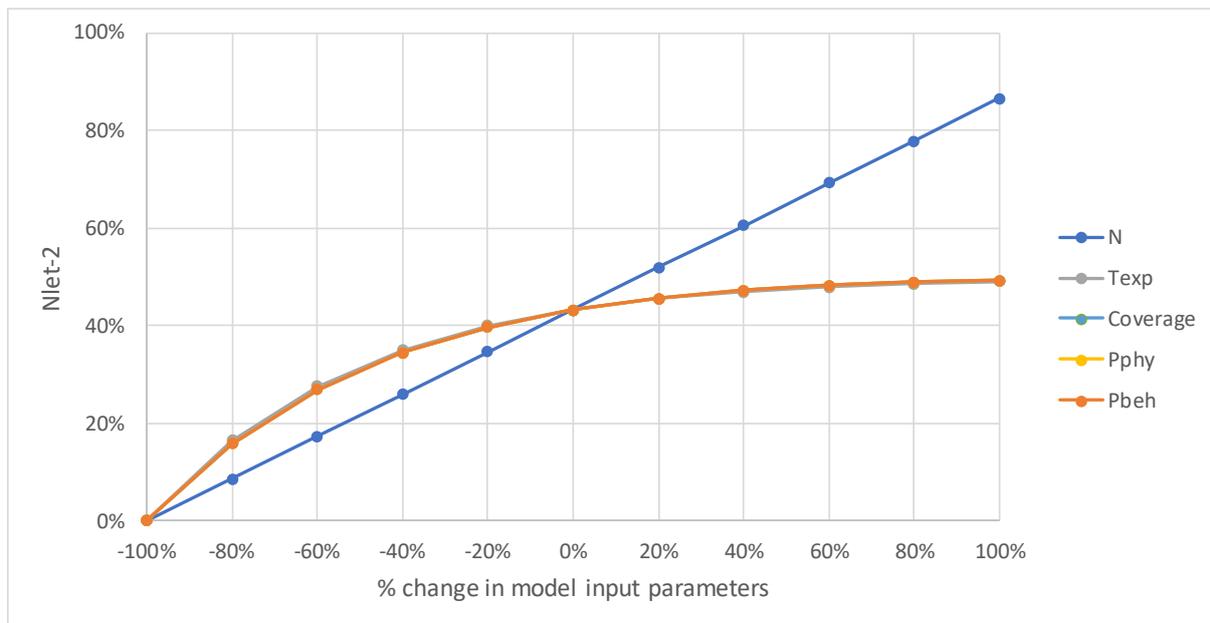
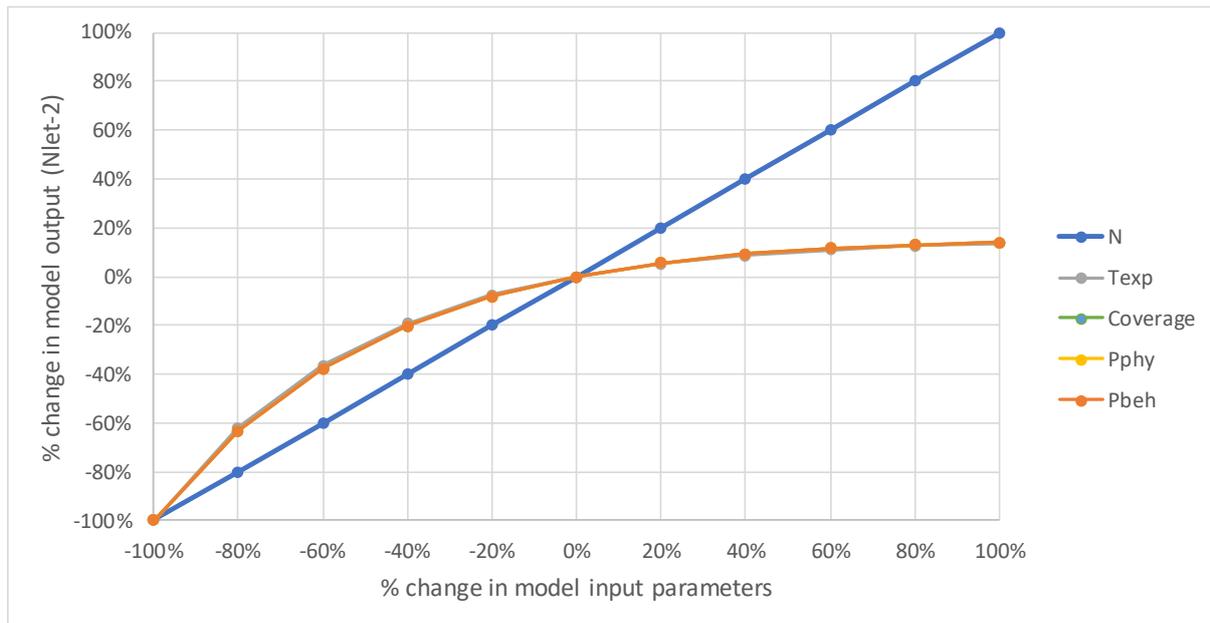


Figure 6. A spider graph comparing the effects of the individual vulnerability factors, the oil drift statistic coverage and the resource abundance model on the model output results (N_{let-2}). For each input the percentage changes in its value for the base case are plotted on the x-axis and the percentage (top) and absolute (bottom) change in results are plotted on the y-axis.

Pattern per wildlife group

Figure 5 and Figure 6 illustrate how the acute mortality (N_{let-1} and N_{let-2}) increases when a model input parameter is increased over the full range of possible values for all wildlife groups. An illustration of how the acute mortality (N_{let-1} and N_{let-2}) for the different wildlife groups varies with the model input data (Coverage, N and exposure time T_{exp}) is presented in Figure 7 - Figure 19.

The solid lines represent the intermediate value of the individual vulnerability factors (P_{beh} and P_{phy}) and the dotted lines the minimum and maximum, defined as the intermediate value $\pm 25\%$. The model input data are held constant at the same base values as in Table 3 (i.e. coverage = 0.5, N = 0.5 and T_{exp} = 15 days) when changing the value of another model input data.

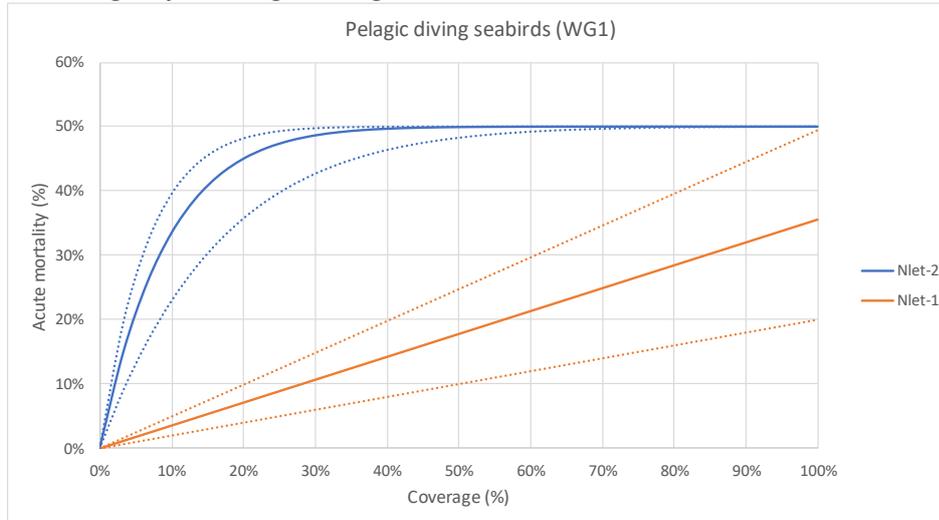
As above Equation 2.2 yields an exponential mortality curve (N_{let-2}) when plotting the acute mortality against coverage and exposure time and a linear mortality curve plotting the acute mortality against N (number of individuals or population fraction). Equation 2.1 yields a linear mortality curve (N_{let-1}).

The shape of the curves for the different VECs depends on the individual vulnerability. The slope values (mortality rate) for each plot is presented in Table 4. The wildlife groups are sorted after their individual vulnerability towards oil spill. Note that the threshold values for lethal oil film thickness are different for birds and mammals and thus their values are not directly comparable.

Table 4. Slope values (relative mortality rates) for the diagrams in Figure 7 - Figure 19 sorted by their individual vulnerability towards oil spill.

Wildlife groups		Coverage		N		Texp
		N_{let-1}	N_{let-2}	N_{let-1}	N_{let-2}	N_{let-2}
WG1	Pelagic diving seabirds	0.360	11.128	0.360	0.999	0.439
WG12	Aquatic mammals	0.317	9.903	0.317	1.000	0.381
WG3	Coastal diving seabirds	0.302	9.418	0.302	0.997	0.359
WG10	Fur seals	0.281	8.761	0.281	1.000	0.330
WG5	Wetland surface feeding seabirds	0.216	6.700	0.216	0.974	0.243
WG2	Pelagic surface foraging seabirds	0.200	6.269	0.200	0.966	0.226
WG6	Wading seabirds	0.158	4.832	0.158	0.924	0.171
WG4	Coastal surface feeding seabirds	0.129	3.913	0.129	0.873	0.138
WG11	Sea cows	0.021	0.601	0.021	0.273	0.021
WG13	Sea turtles	0.015	0.421	0.015	0.201	0.015
WG9	True seals, walruses and sea lions	0.013	0.357	0.013	0.173	0.013
WG8	Toothed whales	0.002	0.067	0.002	0.035	0.002
WG7	Baleen whales	0.001	0.035	0.001	0.002	0.001

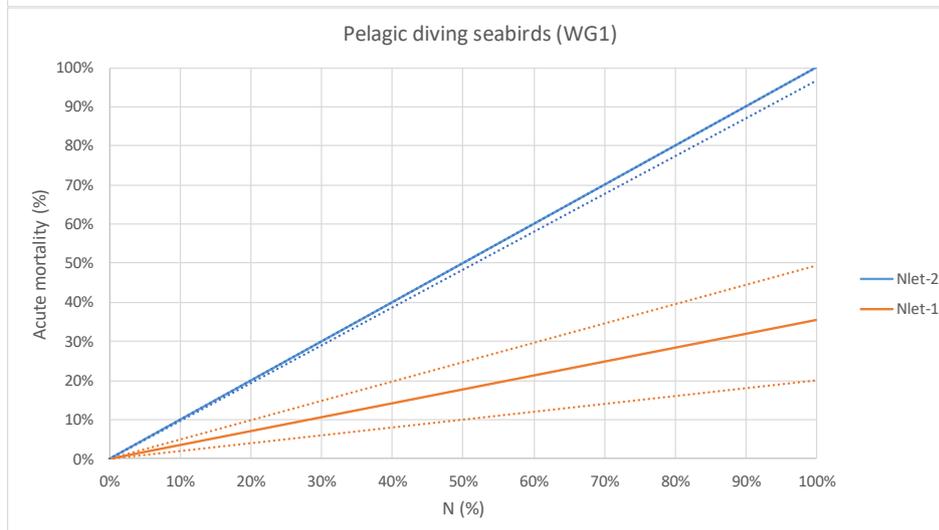
Wildlife group 1: Pelagic diving seabirds



Rel. mortality rate

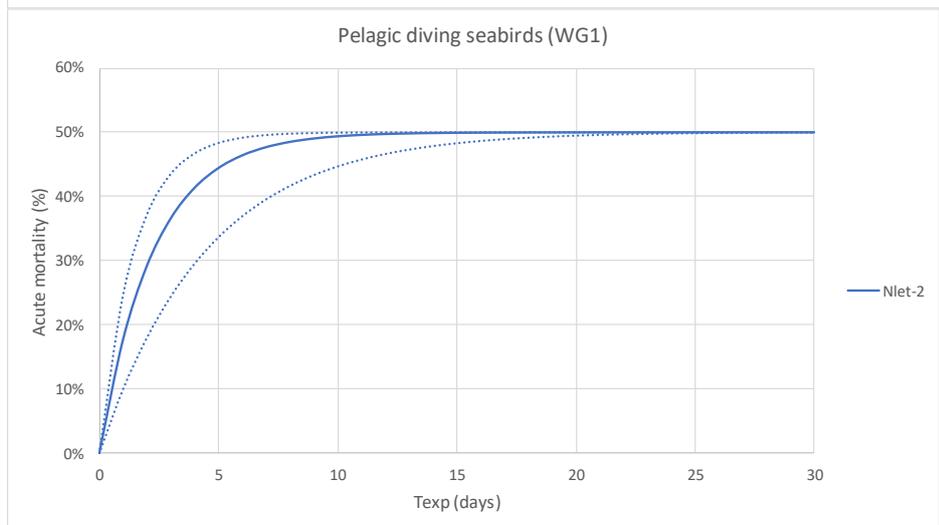
Nlet-1: 0.360

Nlet-2: 11.128



Nlet-1: 0.360

Nlet-2: 0.999

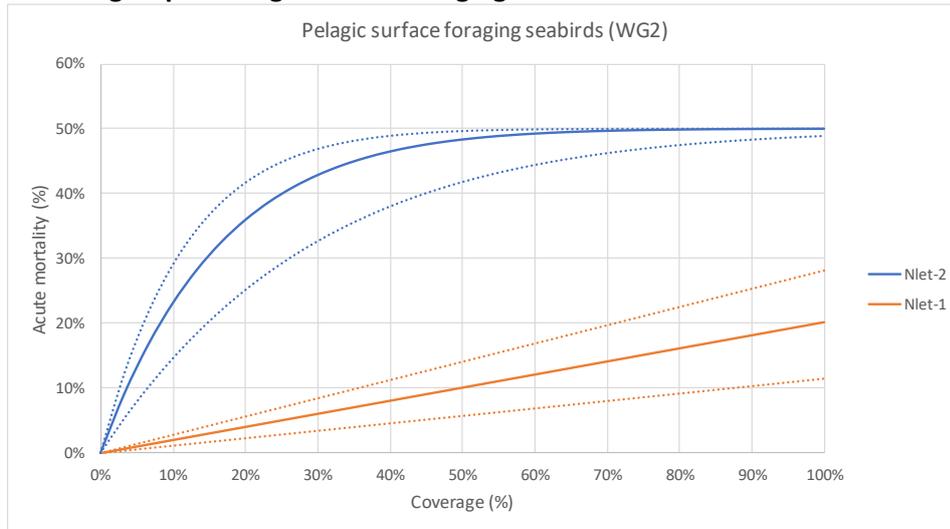


Nlet-2: 0.439

Figure 7. Variation in acute mortality (N_{let-1} and N_{let-2}) for pelagic diving seabirds (WG1) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimate values (IM in Table 2) for WG1 \pm 25%.

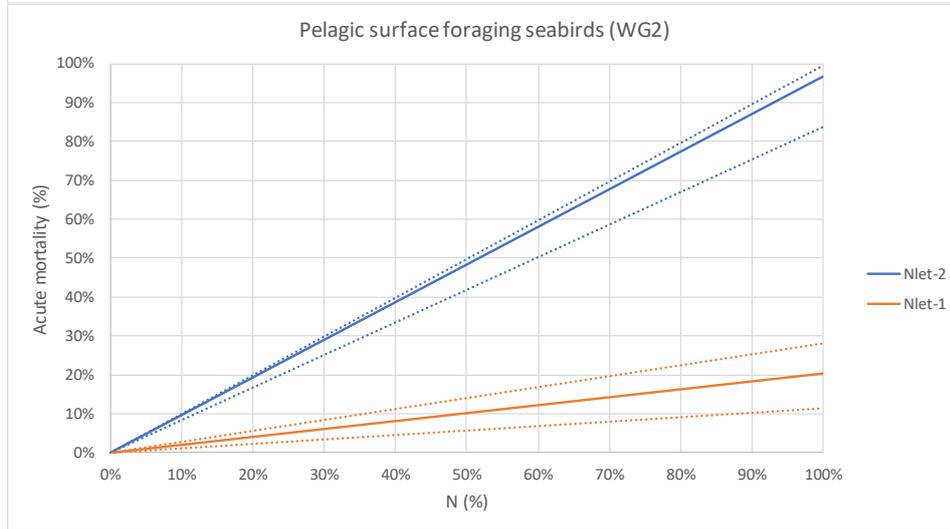
Wildlife group 2: Pelagic surface foraging seabirds

Rel. mortality rate



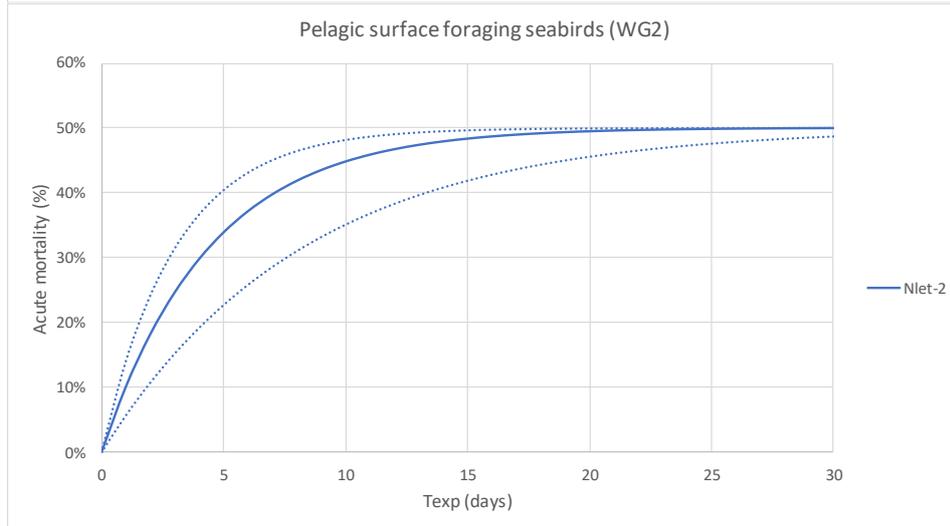
Nlet-1: 0.200

Nlet-2: 6.269



Nlet-1: 0.200

Nlet-2: 0.966

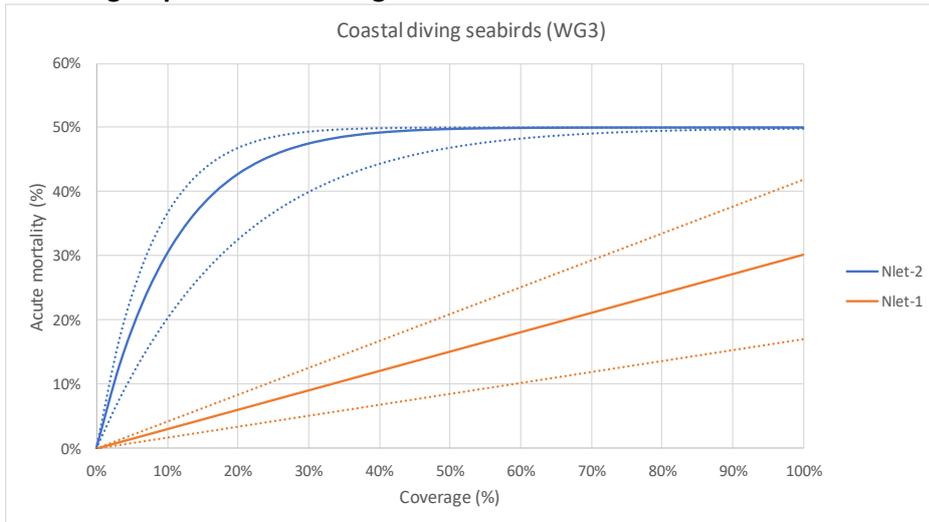


Nlet-2: 0.226

Figure 8. Variation in acute mortality (N_{let-1} and N_{let-2}) for pelagic surface feeding seabirds (WG2) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimate values (IM in Table 2) for WG2 \pm 25%.

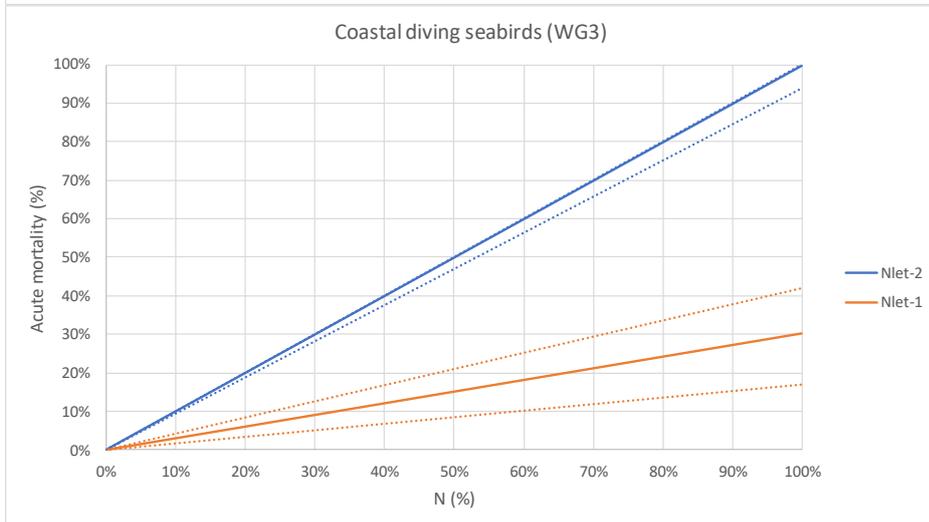
Wildlife group 3: Coastal diving seabirds

Rel. mortality rate



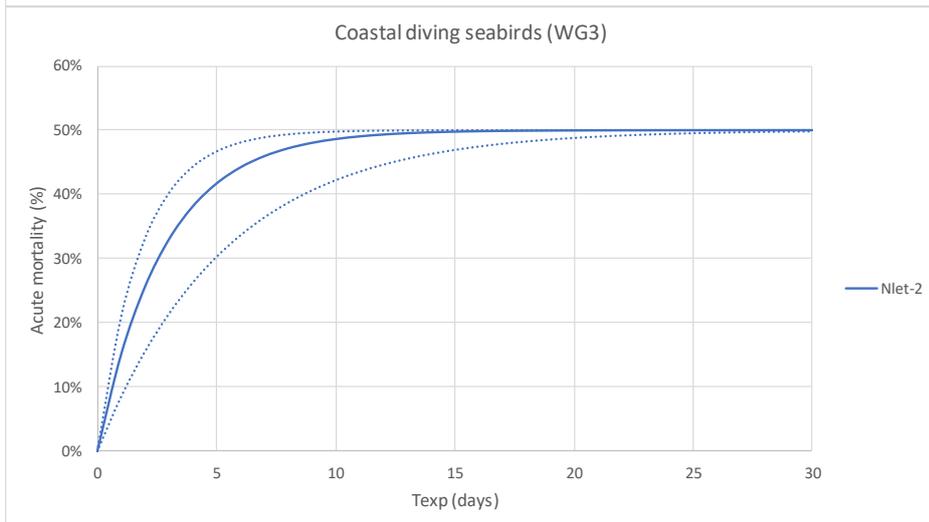
Nlet-1: 0.302

Nlet-2: 0.915



Nlet-1: 0.302

Nlet-2: 0.997

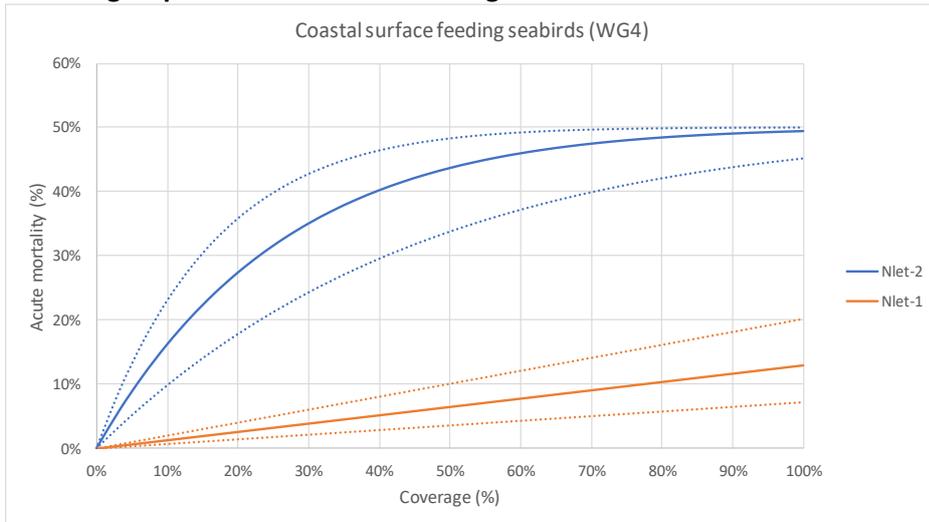


Nlet-2: 0.359

Figure 9. Variation in acute mortality (N_{let-1} and N_{let-2}) for costal diving seabirds (WG3) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimate values (IM in Table 2) for WG3 \pm 25%.

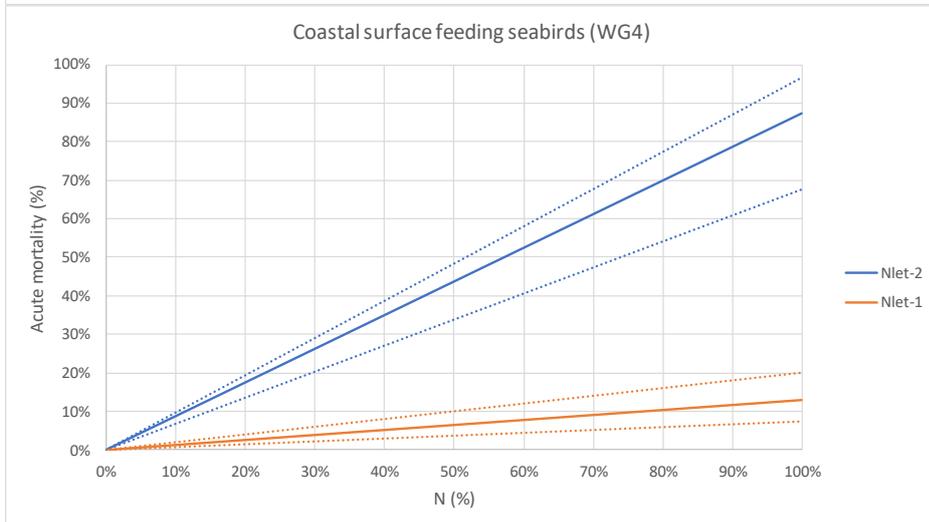
Wildlife group 4: Coastal surface feeding seabirds

Rel. mortality rate



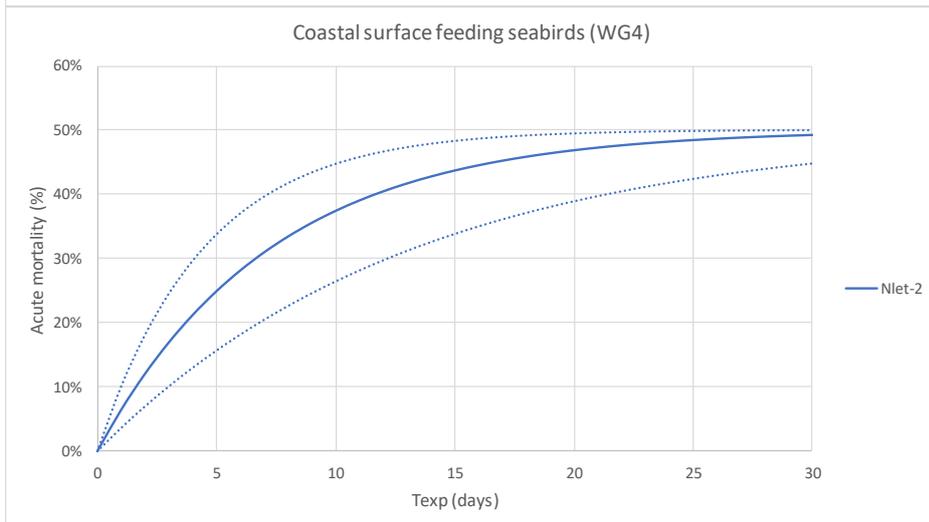
Nlet-1: 0.129

Nlet-2: 3.913



Nlet-1:
0.129

Nlet-2:
0.873

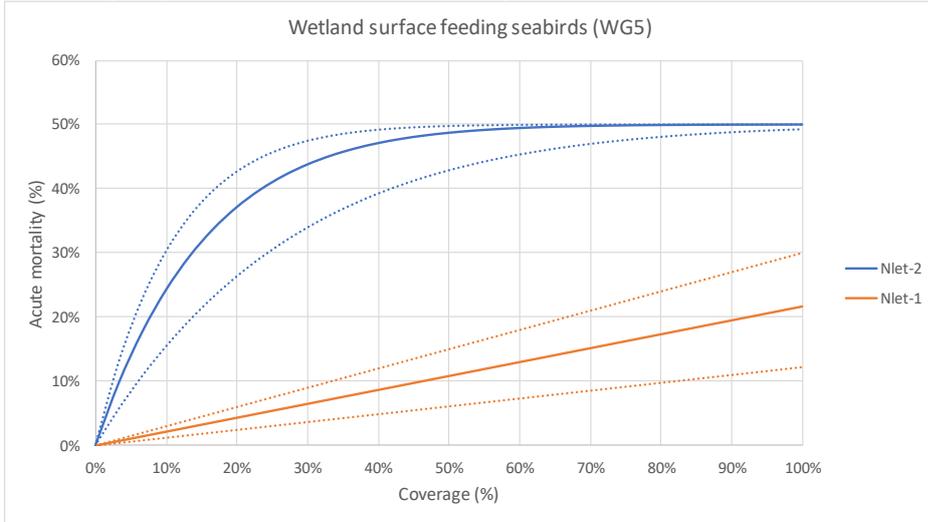


Nlet-2:0.138

Figure 10. Variation in acute mortality (N_{let-1} and N_{let-2}) for costal surface feeding seabirds (WG4) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimates values (IM in Table 2) for $WG4 \pm 25\%$.

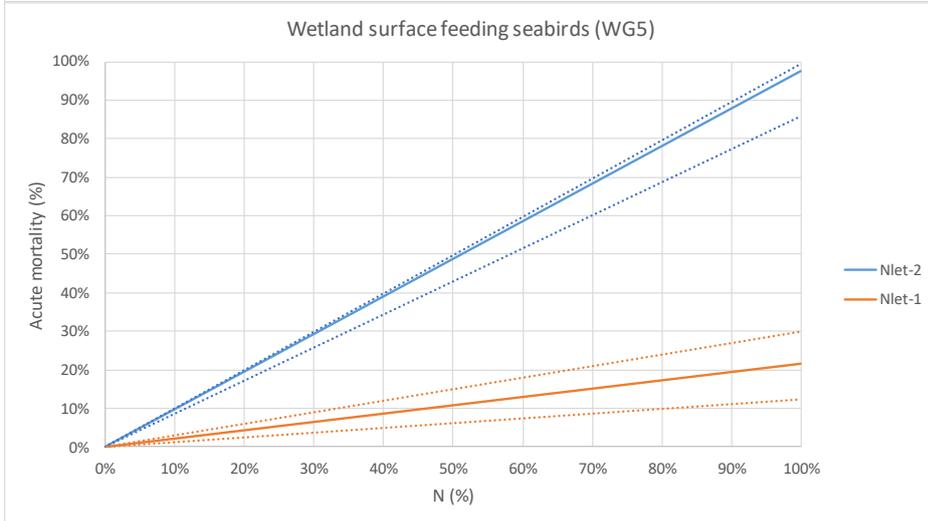
Wildlife group 5: Wetland surface feeding seabirds

Rel. mortality rate



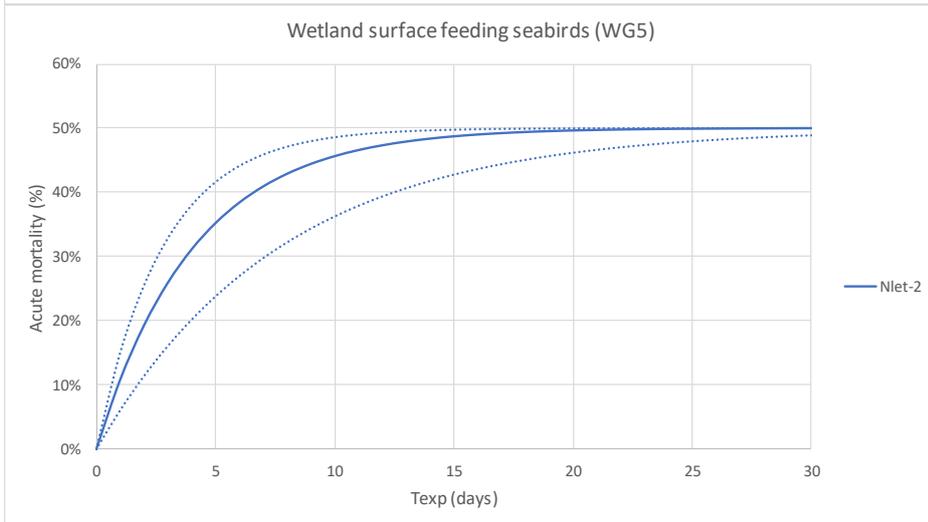
Nlet-1: 0.216

Nlet-2: 6.700



Nlet-1: 0.216

Nlet-2: 0.974



Nlet-2: 0.243

Figure 11. Variation in acute mortality (N_{let-1} and N_{let-2}) for wetland surface feeding seabirds (WG5) with varying model input parameter values for Coverage, N and exposure time (T_{exp}). The values for P_{beh} and P_{phy} are the best estimate values (IM in Table 2) for $WG5 \pm 25\%$.

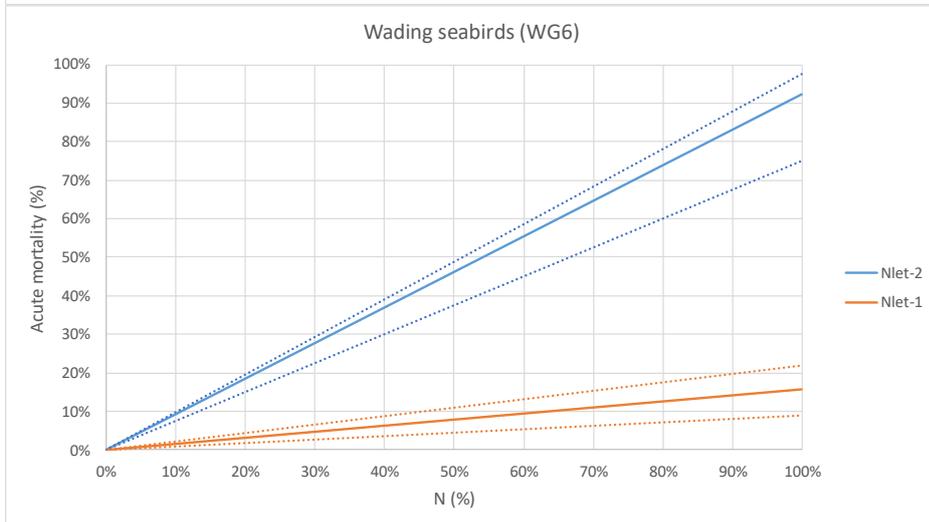
Wildlife group 6: Wading seabirds

Rel. mortality rate



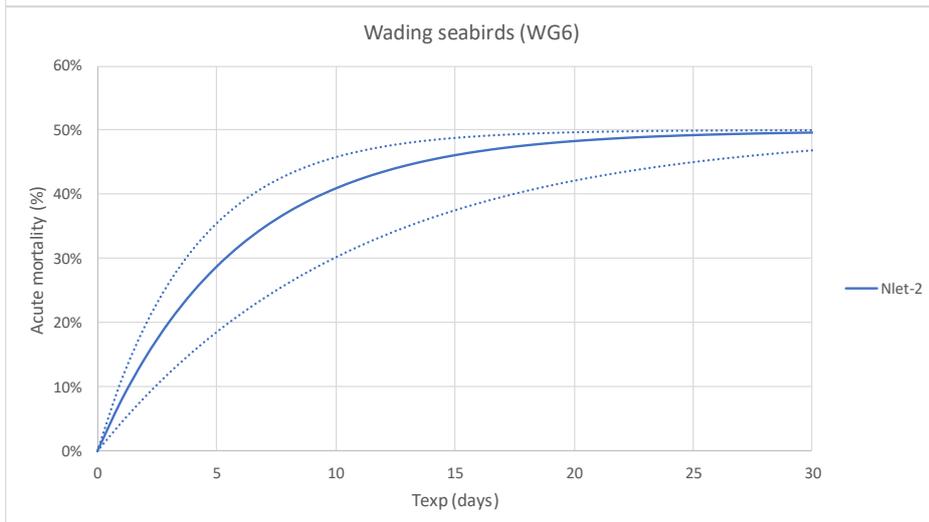
Nlet-1: 0.158

Nlet-2: 4.832



Nlet-1: 0.158

Nlet-2: 0.924

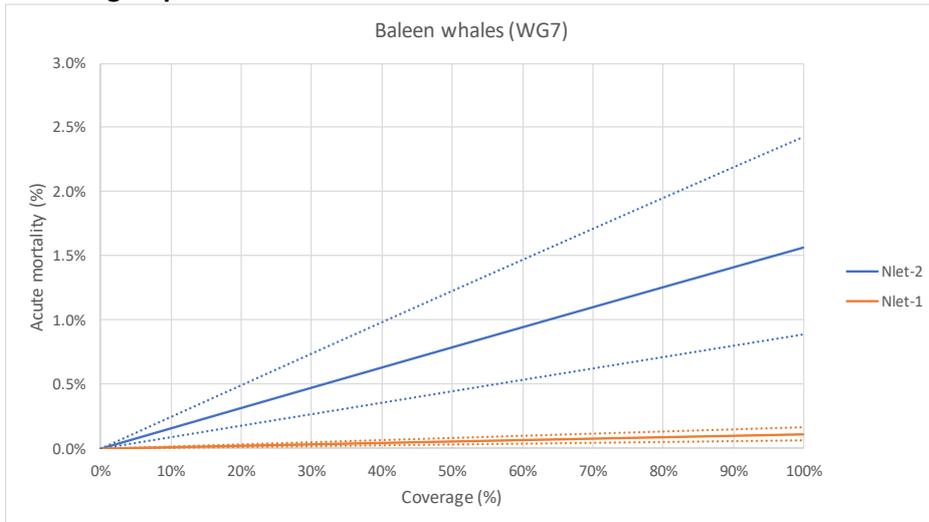


Nlet-2: 0.171

Figure 12. Variation in acute mortality (N_{let-1} and N_{let-2}) for wading seabirds (WG4) with varying model input parameter values for Coverage, N and exposure time (Texp). The value for P_{beh} and P_{phy} is the best estimate value (IM in Table 2) for $WG6 \pm 25\%$.

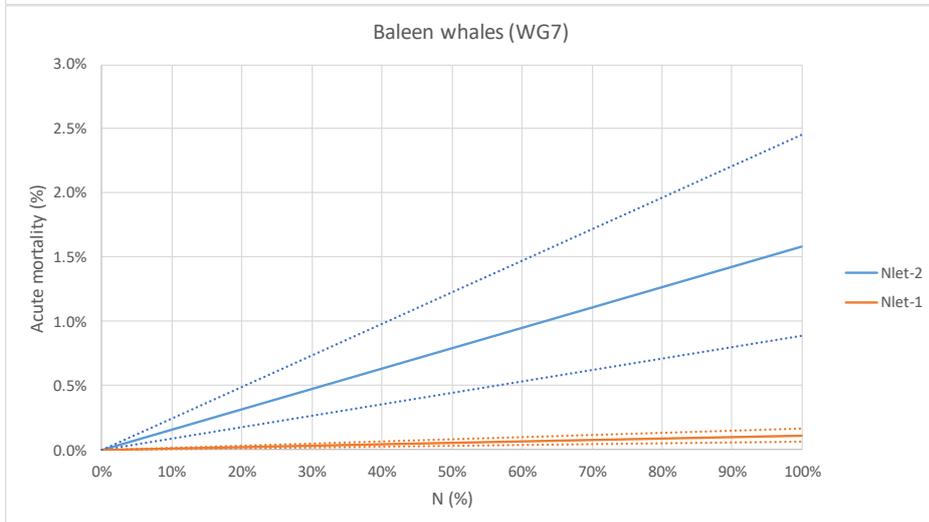
Wildlife group 7: Baleen whales

Rel. mortality rate



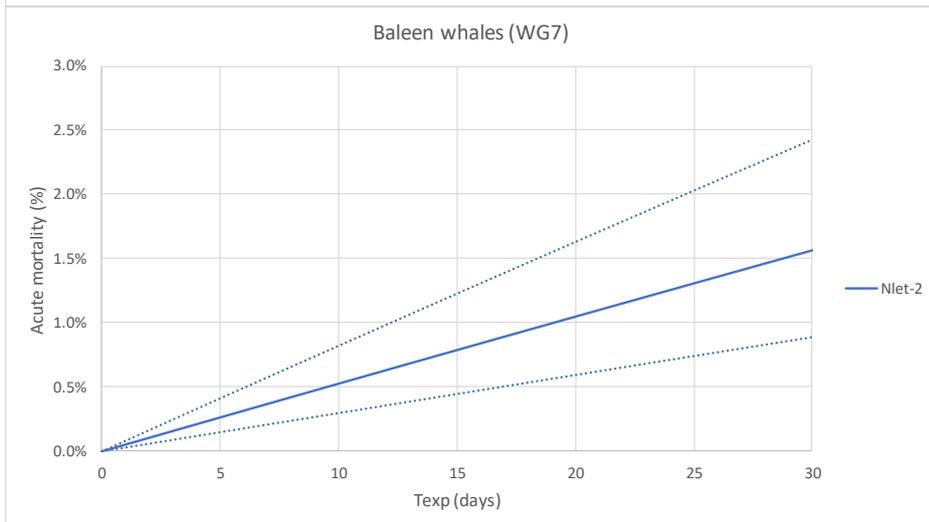
Nlet-1: 0.001

Nlet-2: 0.035



Nlet-1: 0.001

Nlet-2: 0.002

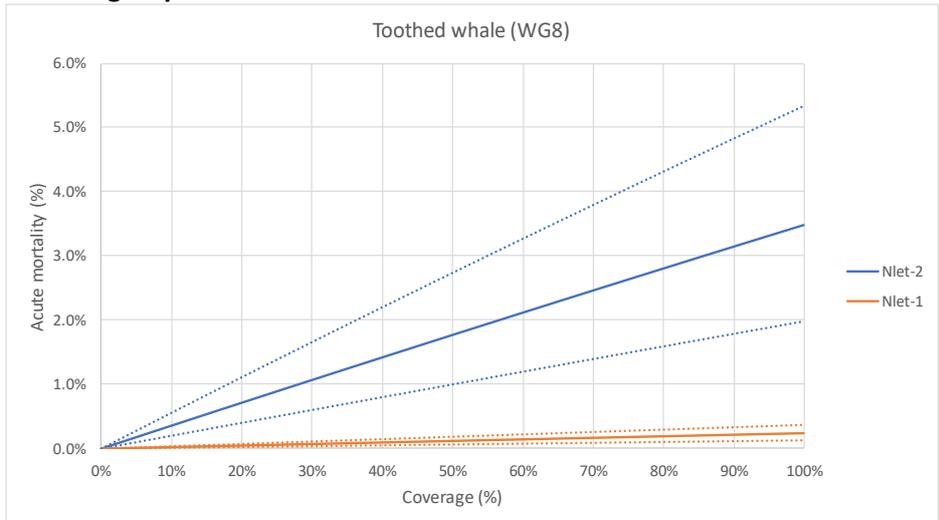


Nlet-2: 0.001

Figure 13. Variation in acute mortality (N_{let-1} and N_{let-2}) for baleen whales (WG7) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimate values (IM in Table 2) for WG7 \pm 25%.

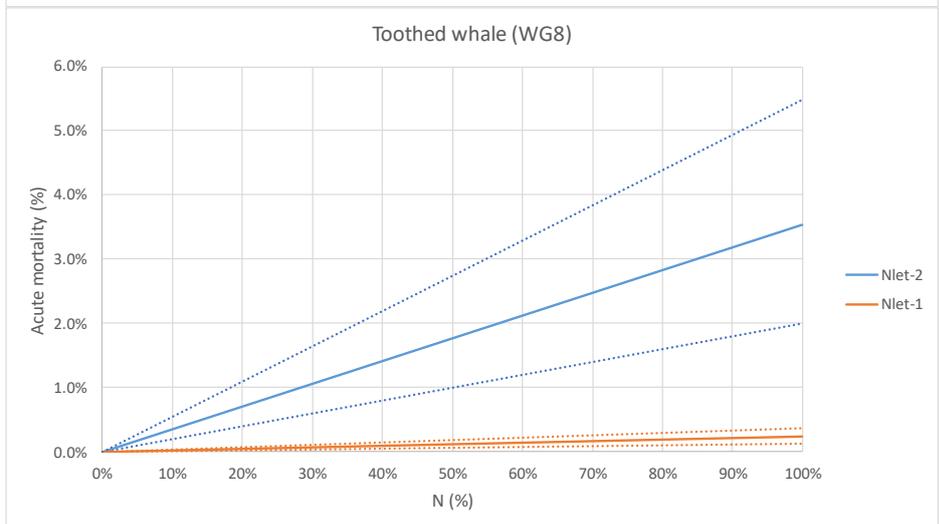
Wildlife group 8: Toothed whales

Rel. mortality rate



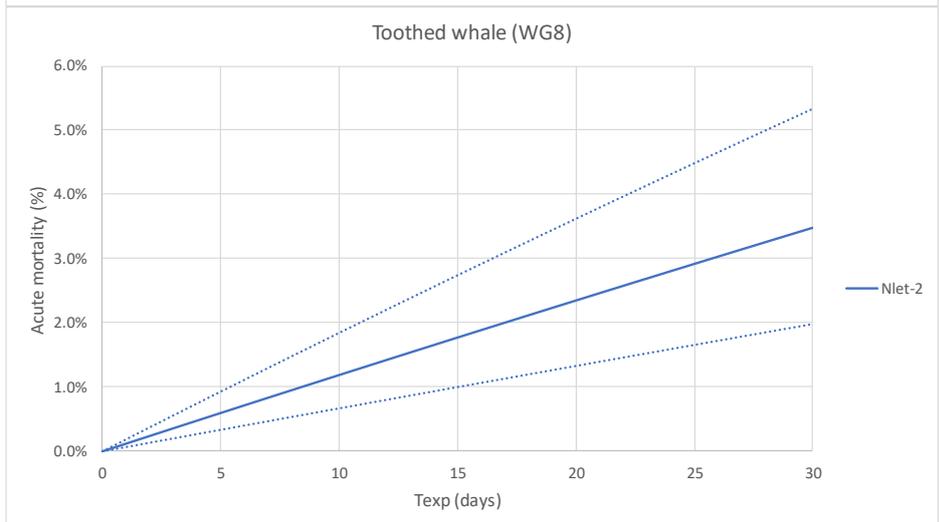
Nlet-1: 0.002

Nlet-2: 0.067



Nlet-1: 0.002

Nlet-2: 0.035

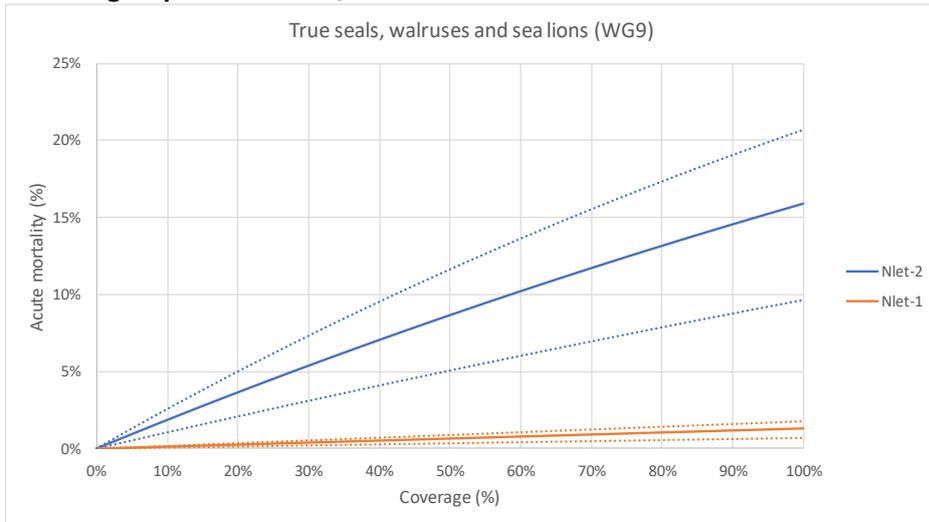


Nlet-2: 0.002

Figure 14. Variation in acute mortality (N_{let-1} and N_{let-2}) for toothed whales (WG8) with varying model input parameter values for Coverage, N and exposure time (T_{exp}). The values for P_{beh} and P_{phy} are the best estimate values (IM in Table 2) for $WG8 \pm 25\%$.

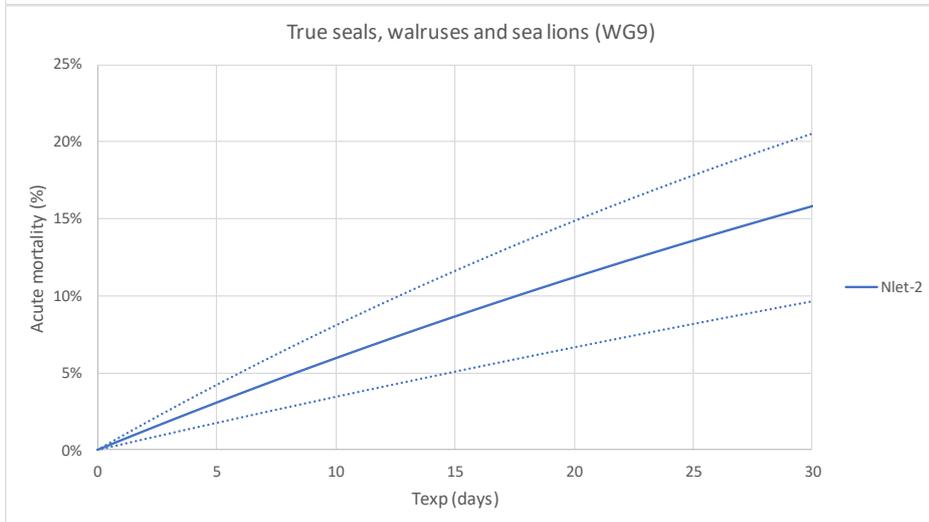
Wildlife group 9: True seals, walruses and sea lions

Rel. mortality rate



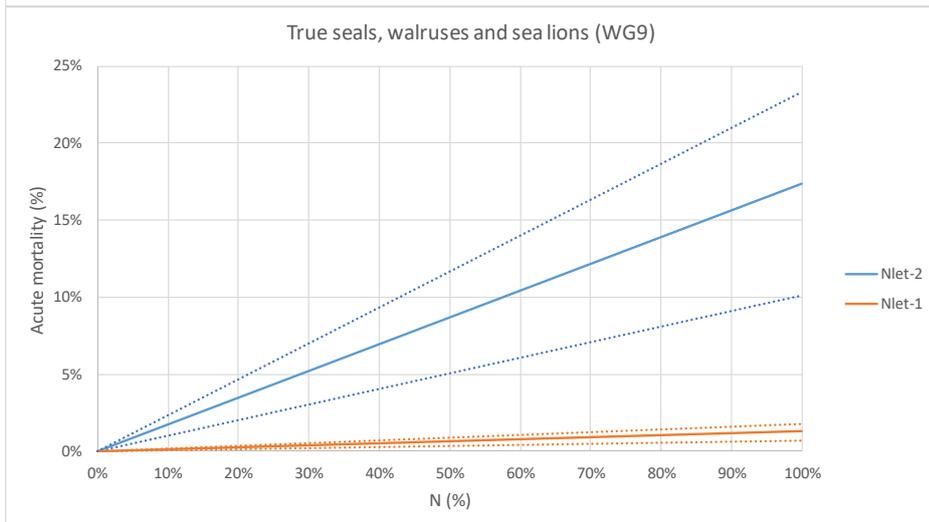
Nlet-1: 0.013

Nlet-2: 0.357



Nlet-1: 0.013

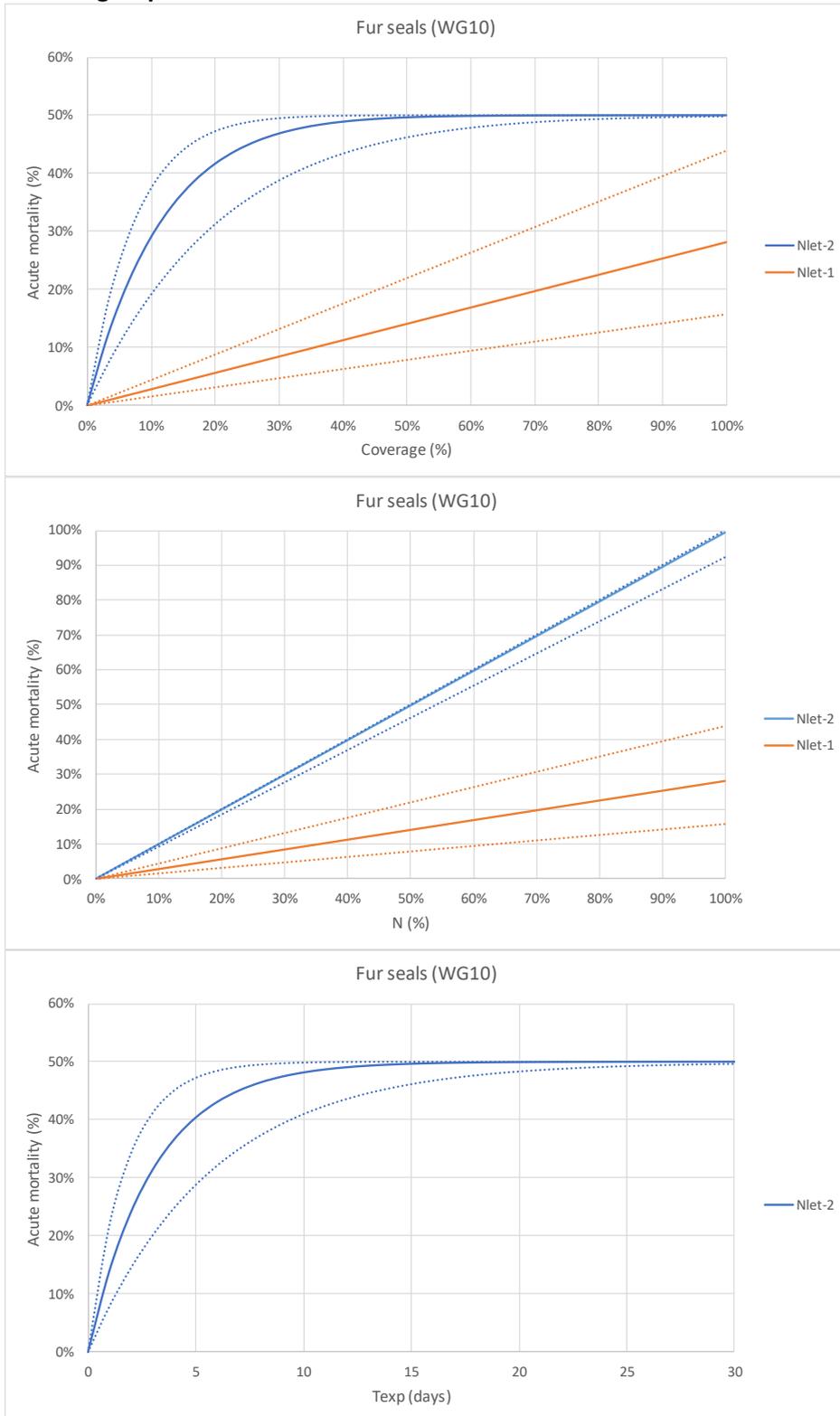
Nlet-2: 0.173



Nlet-2: 0.013

Figure 15. Variation in acute mortality (N_{let-1} and N_{let-2}) for true seals, walruses and sea lions (WG9) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimates value (IM in Table 2) for $WG9 \pm 25\%$.

Wildlife group 10: Fur seals



Rel. mortality rate

Nlet-1: 0.281

Nlet-2: 8.761

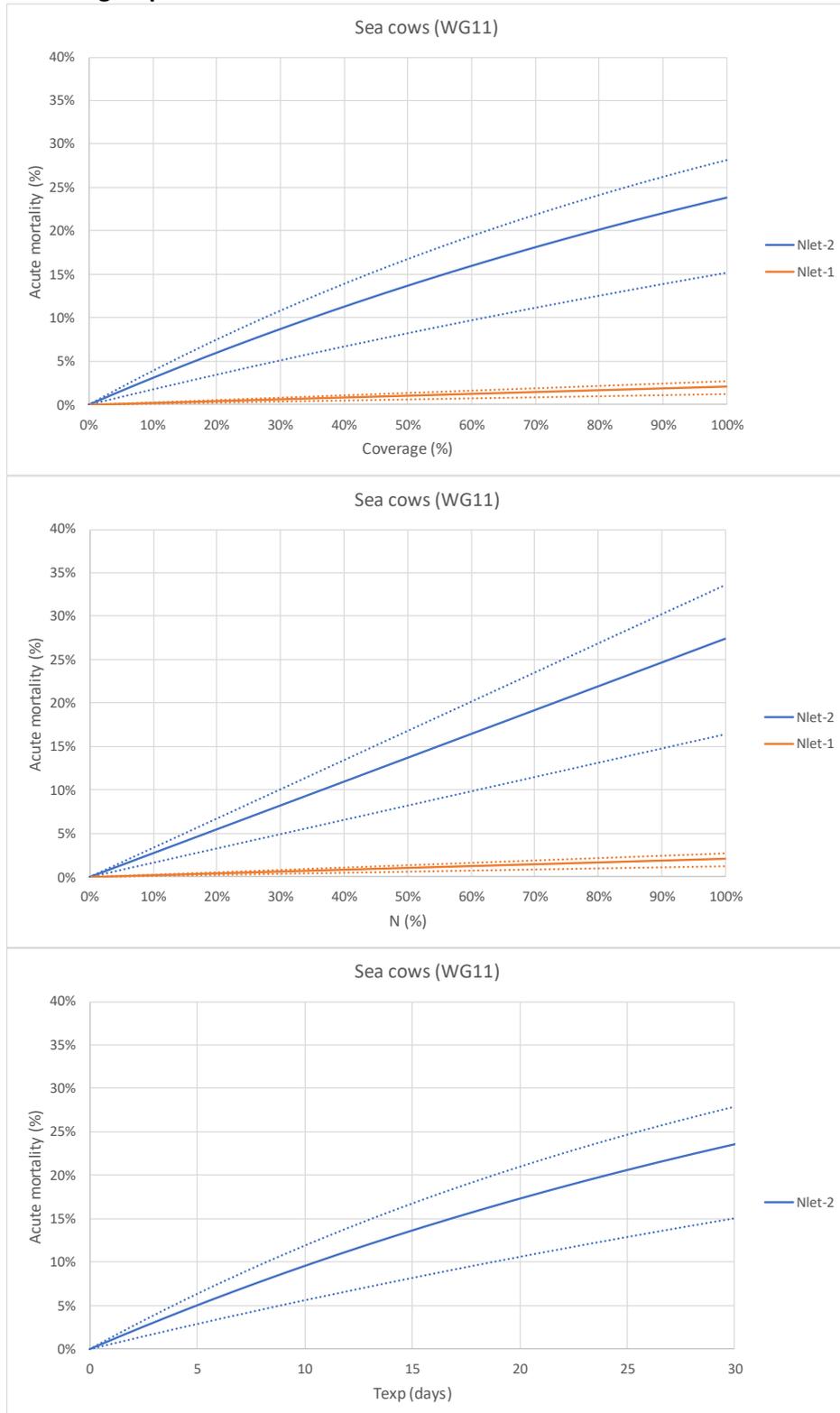
Nlet-1: 0.281

Nlet-2: 1.000

Nlet-2: 0.330

Figure 16. Variation in acute mortality (N_{let-1} and N_{let-2}) for fur seals (W10) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimate values (IM in Table 2) for WG10 \pm 25%.

Wildlife group 11: Sea cows



Rel. mortality rate

Nlet-1: 0.021

Nlet-2: 0.601

Nlet-1: 0.021

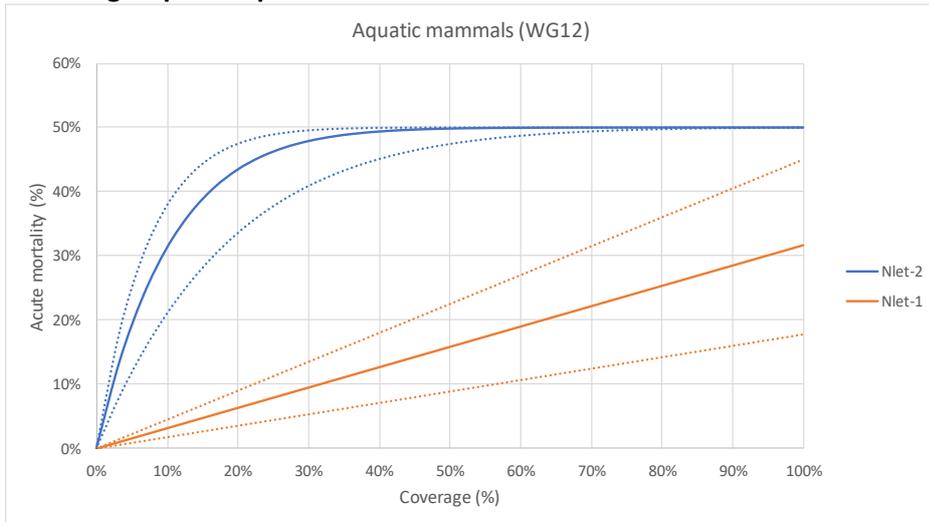
Nlet-2: 0.273

Nlet-2: 0.021

Figure 17. Variation in acute mortality (N_{let-1} and N_{let-2}) for sea cows (WG11) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimate values (IM in Table 2) for $WG11 \pm 25\%$.

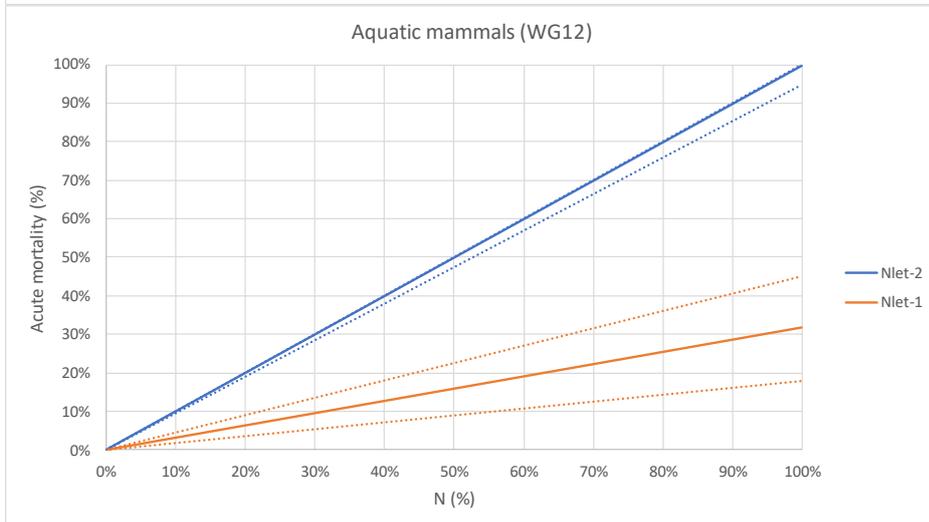
Wildlife group 12: Aquatic mammals

Rel. mortality rate



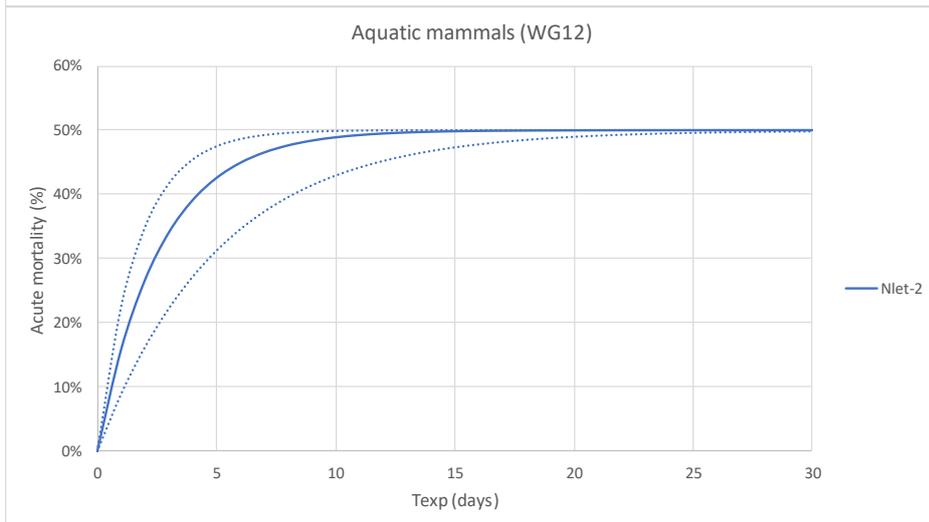
Nlet-1: 0.317

Nlet-2: 9.903



Nlet-1: 0.317

Nlet-2:1.000

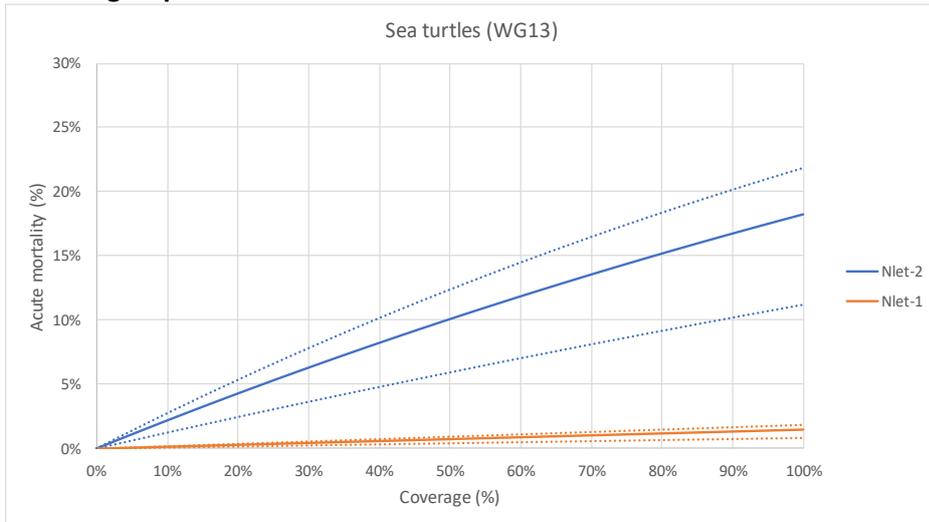


Nlet-2:0.381

Figure 18. Variation in acute mortality (N_{let-1} and N_{let-2}) for aquatic mammals (WG12) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimate value (IM in Table 2) for $WG12 \pm 25\%$.

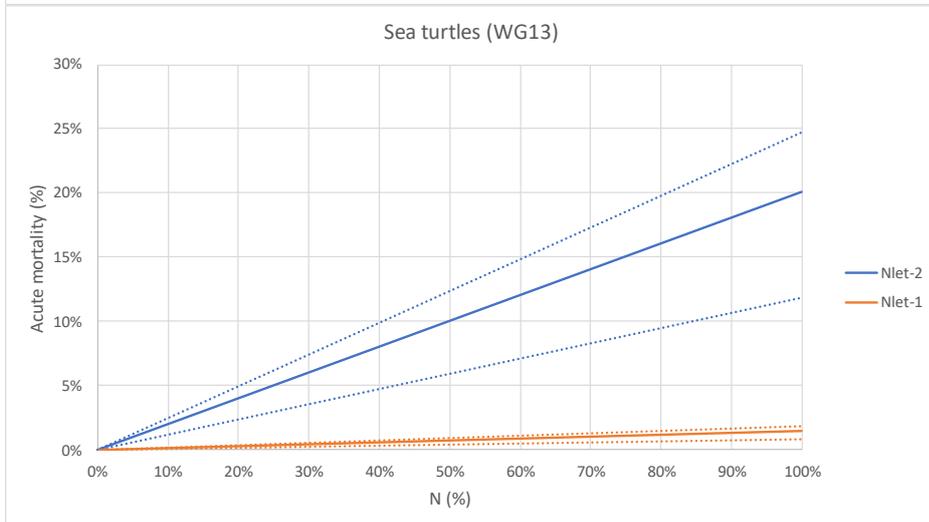
Wildlife group 13: Sea turtles

Rel. mortality rate



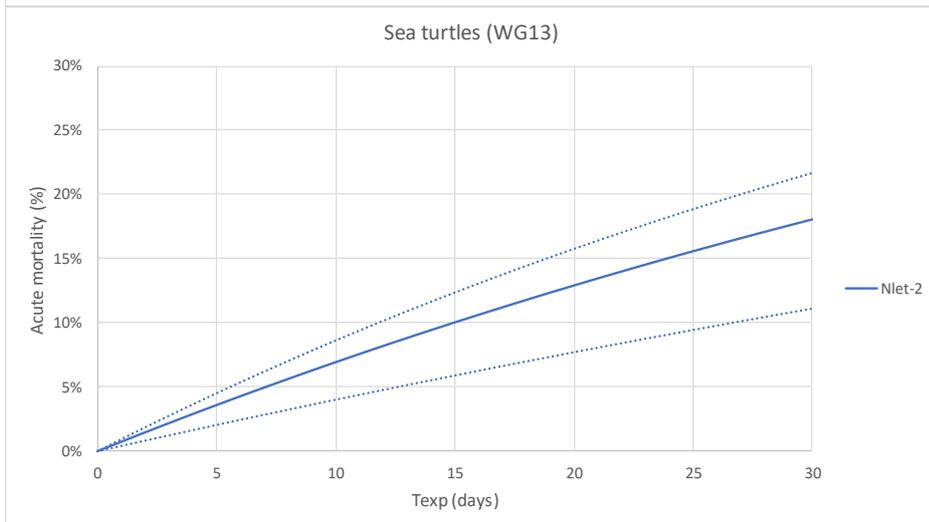
Nlet-1: 0.015

Nlet-2: 0.421



Nlet-1: 0.015

Nlet-2: 0.201



Nlet-2: 0.015

Figure 19. Variation in acute mortality (N_{let-1} and N_{let-2}) for sea turtles(WG13) with varying model input parameter values for Coverage, N and exposure time (Texp). The values for P_{beh} and P_{phy} are the best estimate values (IM in Table 2) for WG13 \pm 25%.

2.1.2 Stochastic uncertainty and sensitivity analysis

Stochastic uncertainty and sensitivity analyses are performed to investigate and rank the relative importance of the model parameters and oil drift parameters. For the stochastic analyses each parameter investigated have been assigned a probability distribution based on different goodness of fit tests and expert judgment.

The range and the probability distribution of the individual behaviour factors are derived from Table 2. Both factors were assigned a triangular distribution with a minimum value equal to the minimum value of Low estimates, the mode or most likely value equal to the median of all estimates and the maximum value equal to the maximum of High estimates (cf. Table 3).

The range and probability of the oil drift parameters were derived from the oil drift dataset constructed for the Deepwater Horizon and from modelled oil drift for the Norwegian coastal dataset. The exposure time was assigned a log-normal distribution with a mean value of 5 days and a standard deviation of 8 days. The coverage was assigned a triangular distribution with a minimum value of 0.10%, a mode or most likely value 0.11% and a maximum value of 100%. The resulting probability distributions used in the analyses are illustrated in Figure 20. The relative abundance of the VECs is held as constant at 1 (cf. Table 3).

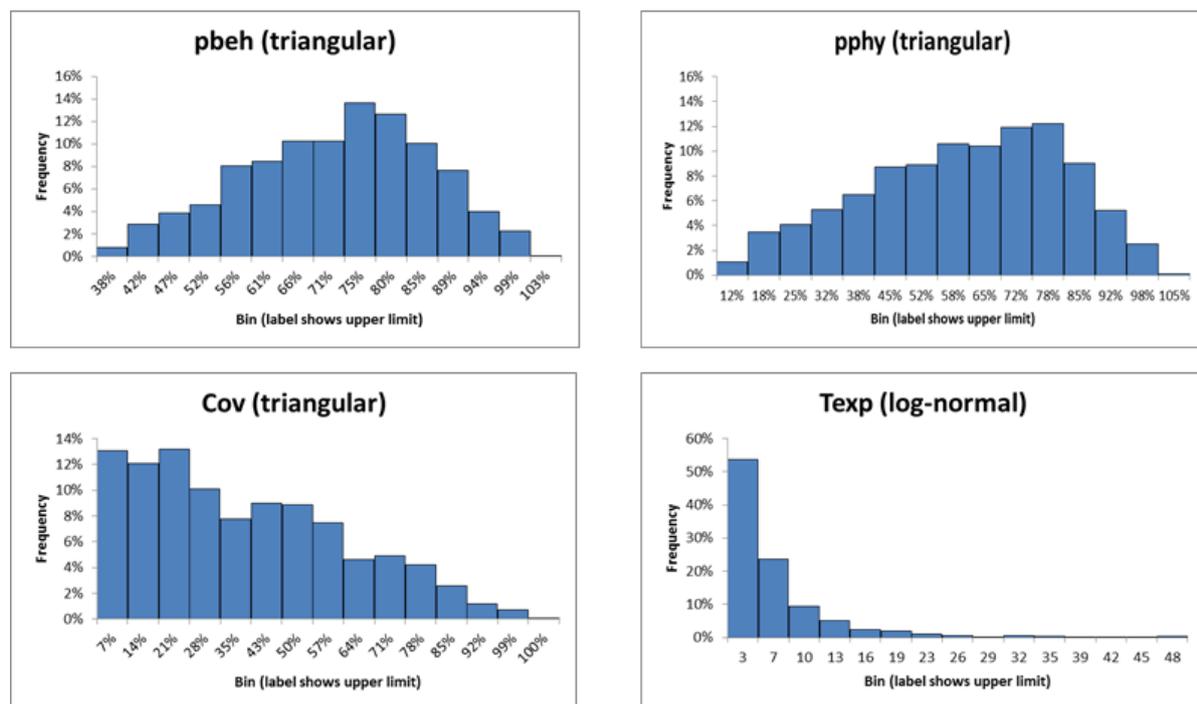


Figure 20. Probability distributions used in the stochastic uncertainty and sensitivity analysis.

The results from the Monte Carlo Simulation (n = 1000) is presented Figure 21. Figure 21 shows the relative frequency (probabilities of the possible outcomes) for the two endpoints as a result of the variation in the input variables. The mean relative population loss for N_{let-1} is $13\% \pm 11\%$, with a “subjective 95% confidence interval” that range from 0 to 43%. The mean relative population loss for N_{let-2} is $32\% \pm 30\%$, with a “subjective 95% confidence interval” that range from 0 to 98%. The term subjective confidence interval is used since the interval is not a real statistical confidence interval.

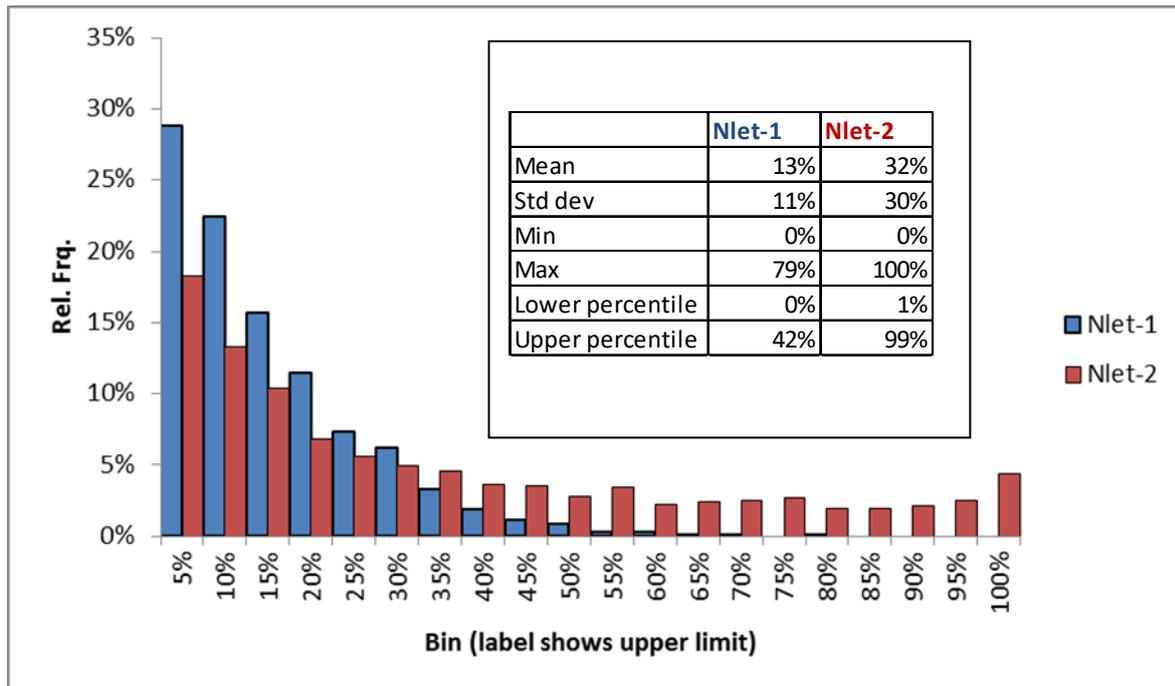


Figure 21. Histogram of the endpoint results given the uncertainty range in the input parameters.

The result from the sensitivity analyses is presented in Figure 22. The result from the Spearman correlation coefficient analysis is presented with p-values and importance rank. The pie diagram shows the sensitivity index from the Factor Prioritization by Reduction of Variance.

All the model parameters and oil drift impact parameters have an effect which are statistically significant. The population loss is more sensitive to the variation in the oil drift impact parameters than to the variation in the two model parameters. The coverage is ranked as the most important variable for N_{let-1} and as much as 73% of the total variance observed in N_{let-1} in in Figure 21 can be attributed to this parameter. Thus, although all parameters are initially equally important, the large natural variability (uncertainty) in coverage make it the most important parameter.

The exposure time T_{exp} is ranked as the most important variable for N_{let-2} but also here the coverage is important. Equation 2.2 is an exponential function and thus the relative importance of the parameters is not directly linked to the input parameters uncertainty range and distribution as it is for a linear equation. Approximately 85% of the variation observed in acute mortality estimated with Equation 2.2 can be attributed to the exposure time and coverage. This does not mean that the individual vulnerability factors are not important, but it demonstrates the stochastic nature of the oil drift impact parameters and the large effect this natural variability has on variation in the impact estimates.

Parameter	N _{let-1}			N _{let-2}		
	Spearman Corr. Coeff.	p-values	Importance rank	Spearman Corr. Coeff.	p-values	Importance rank
Pbeh	0.19	0.00	Cov	0.13	0.00	Texp
Pphy	0.39	0.00	pphy	0.28	0.00	Cov
Cov	0.84	0.00	pbeh	0.60	0.00	pphy
Texp	-	-	-	0.68	0.00	pbeh

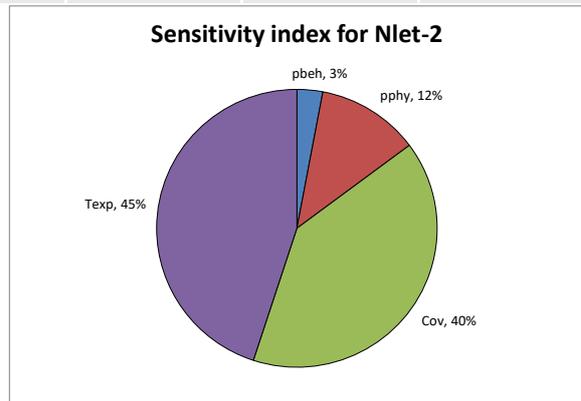
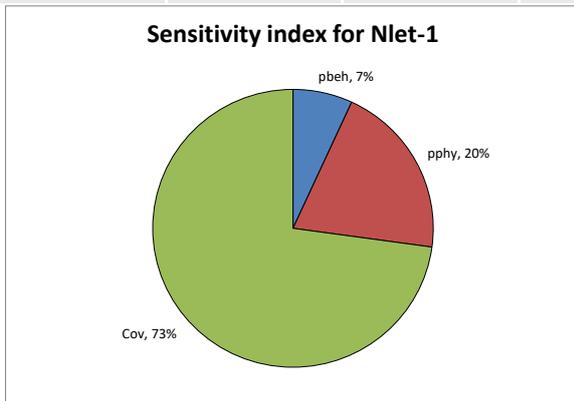


Figure 22. Result for the sensitivity analysis of Nlet-1 and Nlet-2 for the following random variables: p_{beh}, p_{phy}, coverage (Cov) and exposure time (Texp). The relative abundance is held constant at 1.

3 Oil drift impact parameters

ERA Acute uses the following three oil drift statics from the stochastic oil drift simulations to estimate the impact (acute mortality).

1. Time averaged oil film thickness
2. Time averaged coverage above a threshold thickness T
3. Exposure time of oil film above a threshold thickness T

The oil film thickness in a grid cell is used to determine if the oil present in the cell is harmful for the relevant VECs in the cell, while the area and the exposure time is used to estimate the relative size of the impact according to equation 2.1 and 2.2 (Table 5). A summary of the oil drift statistics used by ERA Acute and the corresponding statistics used by MIRA for comparison is presented in Table 5. ERA Acute utilises the oil drift model outputs to a larger degree than MIRA, which only uses the time averaged oil mass in the cell to estimate impact. Since the oil mass by itself does not say anything about the area of the cell that are covered with potentially harmful oil (e.g. oil thicker than a harmful threshold thickness) in the cell, MIRA assumes that there is a fixed quantified relationship between oil mass and area will harmful oil. This is a logical assumption but since the relationship will vary depending on factors such as oil type, surface currents and variation in weather conditions, it is of great advantage to let an oil drift model calculate this relationship.

MIRA addresses the large uncertainty by using oil mass categories when calculating the acute mortality, where a given oil mass within a given interval (e.g. 1-100 ton) results in a fixed acute mortality for a given VEC (e.g. 20% for the most vulnerable seabirds). Thus, *n* grid cells with varying mass between 1 and 100 ton will result in identical mortality in all cells using MIRA, while in ERA Acute it will vary according to the coverage and exposure time in each cell (in addition to uncertainty in the individual vulnerability of a VEC which is fixed in MIRA).

The disadvantage is that the calculation gets more dependent and sensitive to the result of the oil drift models (since the estimated values of three oil drift statics is used in contrast to one categorised value). It is therefore crucial that the oil drift model is set-up correctly. A separate work package is established to develop a “best practice” for set-up of OSCAR for use in ERA Acute.

Table 5. The oil drift statistics (derived from an oil drift model) used by ERA Acute and the corresponding statistics used by MIRA for comparison (both methods use stochastic oil drift simulations as input).

ERA Acute	MIRA
1. Lethality is related to the thickness of oil on the sea surface	1. Lethality is related to amount of oil on the sea surface
2. The lower threshold for mortality is 2 or 10 micrometres	2. The lower threshold for mortality is 1 ton
3. The area of harmful oil on the sea surface is calculated by the oil drift model	3. The expected area of harmful oil on the sea surface is derived from oil mass categories: <ol style="list-style-type: none"> 1. 1-100 ton 2. 100-500 ton 3. 500-1000 ton 4. 1000 – inf. ton
4. The exposure time of harmful oil on the sea surface is calculated by the oil drift model	4. Exposure time is indirectly included in the calculation of the amount of oil

3.1 Threshold for oil film thickness

The lethal oil film thickness is 2 and 10 μm for seabirds and marine mammals and sea turtles, respectively. The threshold thickness of 2 μm for seabirds is derived from literature review of other impact models (French-McCay, 2009, 2004; Koops et al., 2004; Scholten et al., 1996), experimental studies (Hughes et al., 1990; Jenssen, 1994; Jenssen and Ekker, 1991a, 1991b), studies of the microstructure of seabird's feathers (O'Hara and Morandin, 2010) and expert judgment (e.g. Peakall et al., 1985; Stephenson, 1997) (cf. Bjørgesæter and Damsgaard Jensen, 2015 for more details). The default threshold level for seabirds in ERA Acute was originally 10 μm (Spikkerud et al., 2010).

The lethal threshold oil film thickness for marine and aquatic mammals was kept at 10 μm based on that these animals rely on their blubber for thermoregulation and the pelage of aquatic mammals which is less sensitive to effects of oil fouling on thermoregulation than the plumage of birds. Also, there was no available data supporting that the original film thickness threshold should be altered (cf. Bjørgesæter and Damsgaard Jensen, 2015 for more details).

To investigate the importance of the threshold oil film thickness value (T), stochastic oil drift simulations with six different *pre-processing thresholds values* have been performed. The threshold thicknesses investigated were 0, 2, 4, 6, 8 and 10 μm .

The endpoints investigated are:

- (1) Number of grid cells with oil film thicker than T
- (2) Sea surface area with oil film thicker than T
- (3) Exposure time of oil film thicker than T
- (4) Impact (population loss)

The number of grid cells above T yields an indication of the geographical extent of harmful oil (oil thicker than the threshold T). The more cells above the threshold, T the larger geographical area is affected by oil. The sea surface area and exposure time of oil film thicker than T is directly linked to the size of the impact (population loss), although the impact may vary considerable depending on the distribution and relative abundance of the VECs in relation to the distribution of oil.

3.1.1 Oil drift simulations

Stochastic oil drift simulations were performed for a topside release of 5000 Sm^3/day for duration of 15 days. The oil type was Oseberg Øst 13 °C. The OSCAR model was set up according to the best practice set-up for performing stochastic oil drift simulations for MIRA analyses (Acona, DNV GL, Akvaplan-niva, 2016), except that the refinement parameter was set to 3. This means that the 9 km^2 grids are divided into $3 \times 3 = 9$ smaller cells for more detailed calculation of film thickness and coverage. The resolution of coverage in the oil drift model is therefore $1/9 = 11\%$ or approximately 1 km^2 (before exported to the larger $10 \times 10 \text{ km}^2$ grid).

A total of 237 simulations were performed for each threshold thickness (release scenario).

Each simulation was run for 15 days (duration of the oil release) and continued for 20 days after the release has been stopped (i.e. the simulation period is $15 + 20 = 35$ days). A follow-time of 20 days is a trade-off between ensuring that the fate of the oil is included in the simulation results without adding extra uncertainty in the predictions (cf. Acona, DNV GL, Akvaplan-niva, 2016). The internal computational time steps were set to 20 minutes and the output time step to 60 minutes. The oil drift simulation results were post-processed with *pysemble v.03*, a Python script developed by SINTEF for the ERA Acute project to ensure correct estimates of oil film thickness, coverage and exposure time in the $10 \times 10 \text{ km}$ UTM grid cells.

Calculating impact: The impact was calculated using the ERA Acute Calculator v.0.59 (Brönner, 2017; Brönner et al., 2017). For each scenario (thickness tested) the following procedure was performed (see also Figure 23):

- (1) Change thickness values (“threshold_map”) in the *seasurface.py*
- (2) Change the threshold value for the VECs in *surface_thickness_thresholds.csv*
- (3) Run the ERA Acute calculator

Statistical analyses were done in R v. 3.4.2 (R Core Team, 2017). Maps for illustrations was constructed using the ERA Acute Tool v. 1.0.0.37.

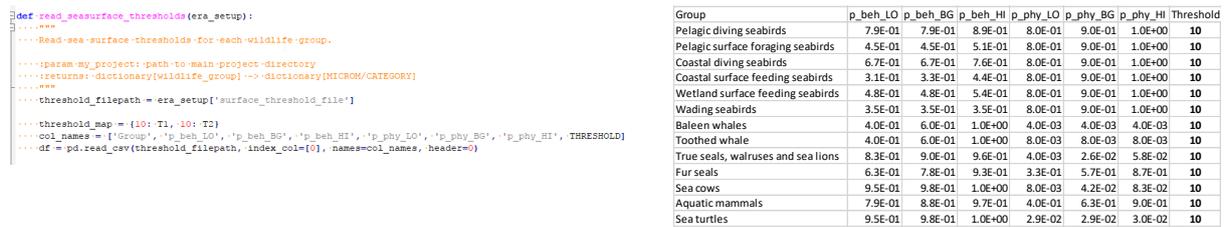


Figure 23. The Python code showing the “threshold_map” in the *seasurface.py* (left) and the “surface_thickness_thresholds.csv” (right) where the threshold thickness was altered for the different tests (here testing Scenario T10).

3.1.2 Results

Effect on oil drift parameters: A summary of the effect of different thickness thresholds on the oil drift parameters is presented in Table 6 and illustrated in Figure 24 (number of grid cells), Figure 25 (area) and Figure 26 (exposure time). All three oil drift parameters decrease with increasing oil film thickness threshold. The effect of lowering the threshold level from 2 to 10 micrometres have a significant effect on all three oil drift statistical endpoints at a 5% significance level (ANOVA with a Tukey's range test). There was no statistically significant difference in the number of grid cells for Scenario T04 and T06 ($p=0.22$), T06 and T08, T10 ($p=0.69$, $p=0.17$) and T08 and T10 ($p=0.94$), while for the area above T, all scenarios were statistically significantly different except Scenario T08 and T10 ($p=0.41$). For exposure time there were no statistically significant difference between Scenario T4 and T6 ($p=0.33$), T06 and T8, T10 ($p=0.65$, $p=0.11$) and Scenario T08 and T10 ($p=0.90$).

Statistical maps for the oil drift parameters constructed from the stochastic oil drift simulations are illustrated in Figure 27, Figure 28 and Figure 29. The area above 2 μm is on average 1.82 times larger than the area above 10 μm ($27,431 \text{ km}^2 \pm \text{SD } 13,562$ versus $15,067 \text{ km}^2 \pm \text{SD } 3,345$) (cf Table 6). Similarly, the exposure time for oil thicker than 2 μm is on average 1.41 times longer than the exposure time for oil thicker than 10 μm ($1.22 \text{ days} \pm \text{SD } 0.50$ versus $0.87 \text{ days} \pm \text{SD } 0.39$) and the number of grid cells above 2 μm versus 10 μm is 1.2 ($931 \text{ cells} \pm \text{SD } 220$ versus $781 \pm \text{SD } 192$) (cf. Table 6).

Table 6. The mean number of grid cells, total area and exposure time with film thickness above the oil film threshold thicknesses (T).

Scenario	Threshold T (µm)	Number of grid cells above T		Area above T (km ²)		Exposure time above T (days)	
		Mean	SD	Mean	SD	Mean	SD
Scenario T00	0	1,284	296	46,335	13,562	1.54	0.50
Scenario T02	2	931	220	27,431	7,066	1.22	0.50
Scenario T04	4	856	206	21,368	5,130	1.06	0.45
Scenario T06	6	811	197	18,256	4,202	0.97	0.42
Scenario T08	8	781	192	16,294	3,695	0.91	0.41
Scenario T10	10	763	188	15,067	3,345	0.87	0.39

Number of 10×10 km grid cells above T

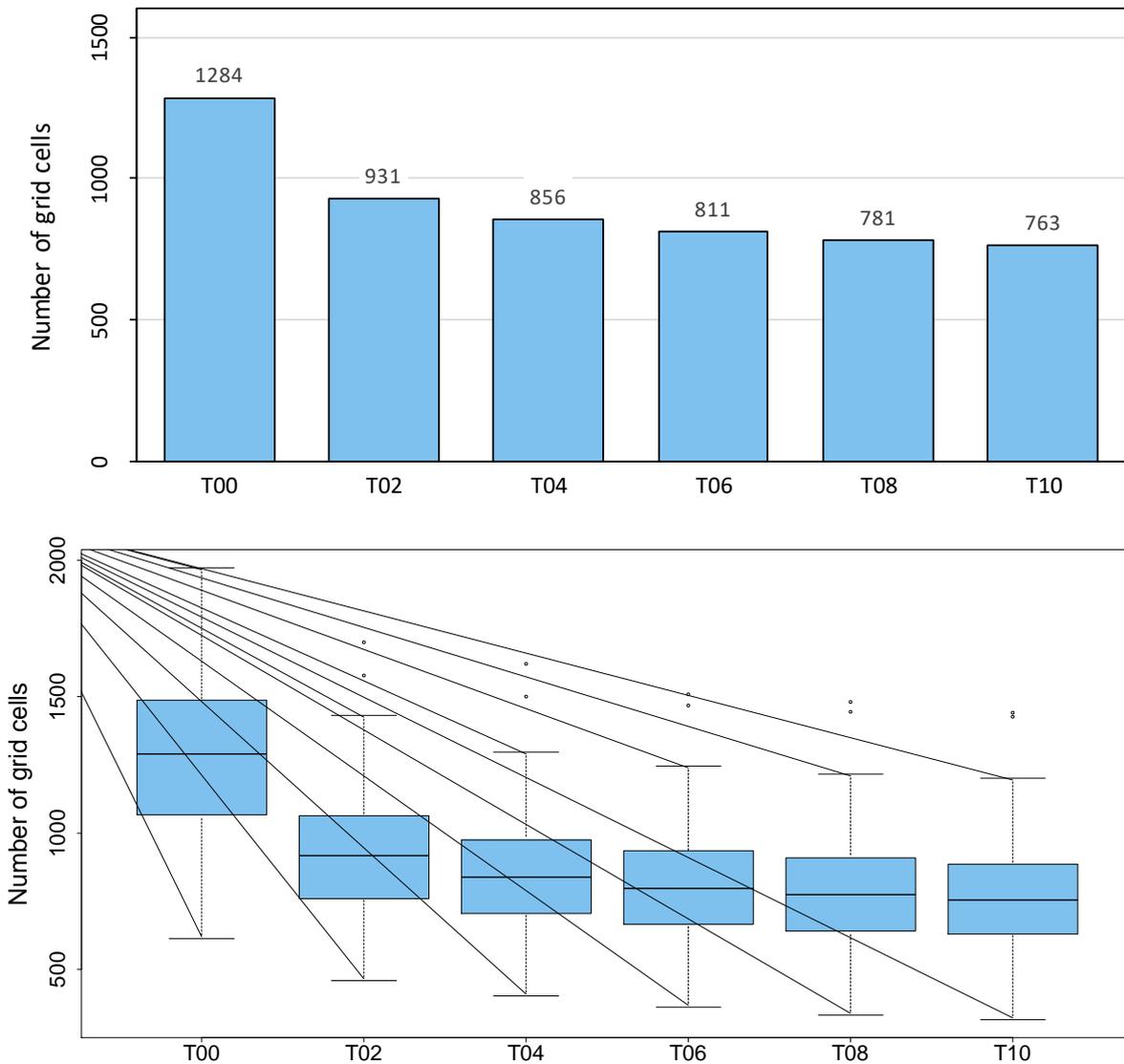


Figure 24. Column plots (top) and box plots (bottom) comparing the number of sea surface grid cells above the threshold thickness (T) for the six scenarios each represented with 237 simulations. The column plot shows the mean values while the box plot illustrates the minimum, first quartile, median (typical value), third quartile, and maximum for the 237 simulations. The whisker length is set at 1.5 times the inter-quartile range (IQR), with black rings showing outliers, including minimum and maximum values.

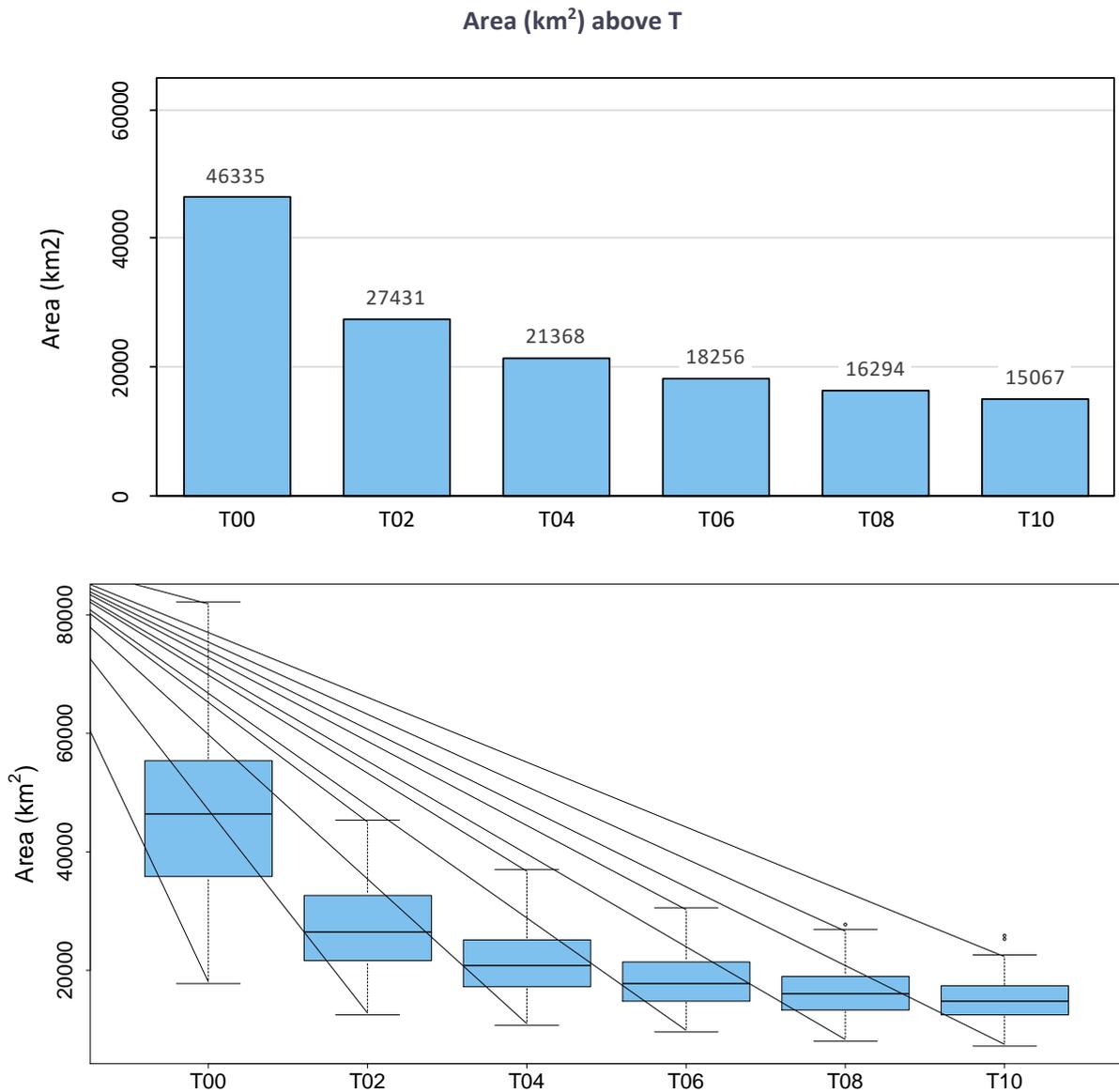


Figure 25. Column plots (top) and box plots (bottom) comparing the sea surface area above the threshold thickness (T) for the six scenarios each represented with 237 simulations. The column plot shows the mean values while the box plot illustrates the minimum, first quartile, median (typical value), third quartile, and maximum for the 237 simulations. The whisker length is set at 1.5 times the inter-quartile range (IQR), with black rings showing outliers, including minimum and maximum values.

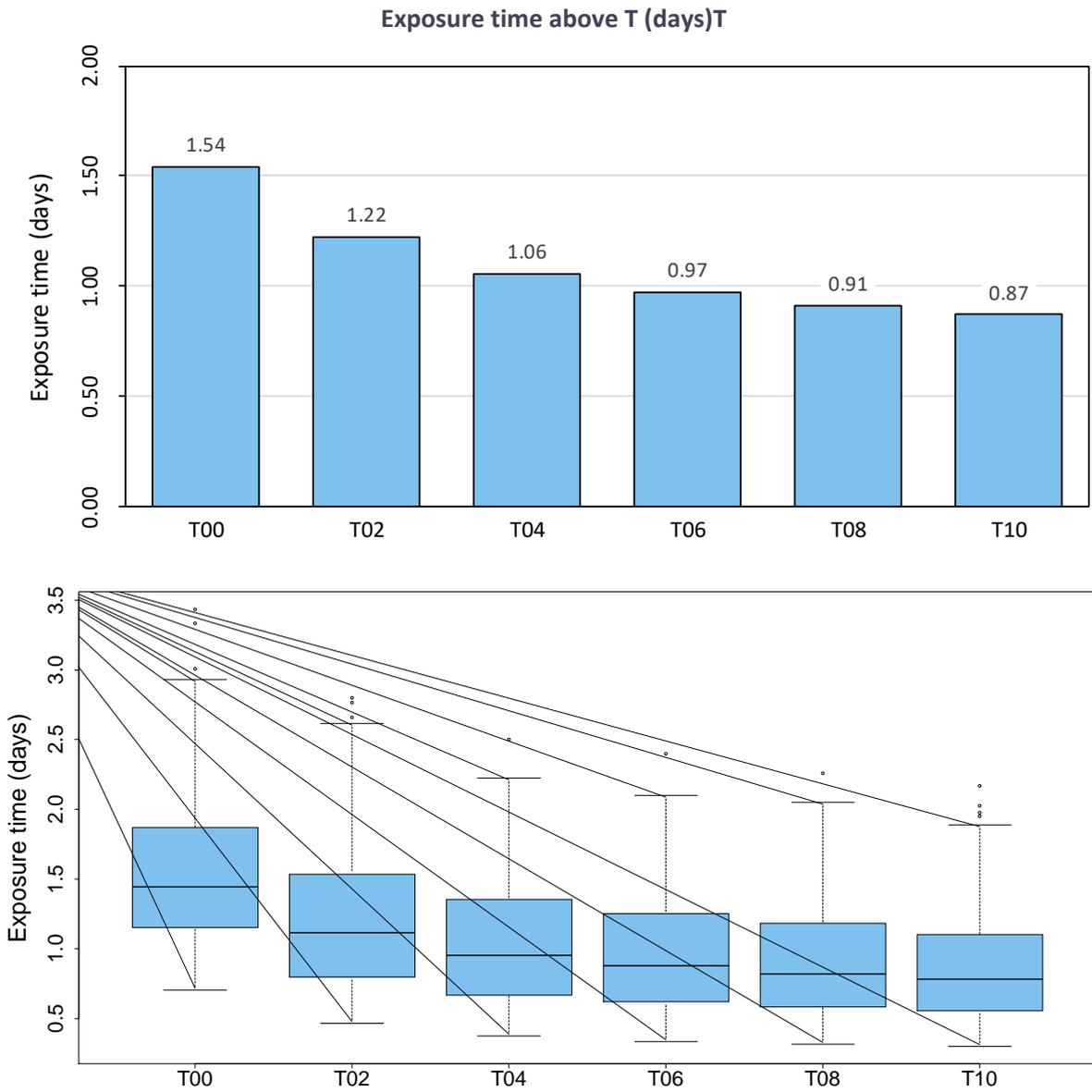
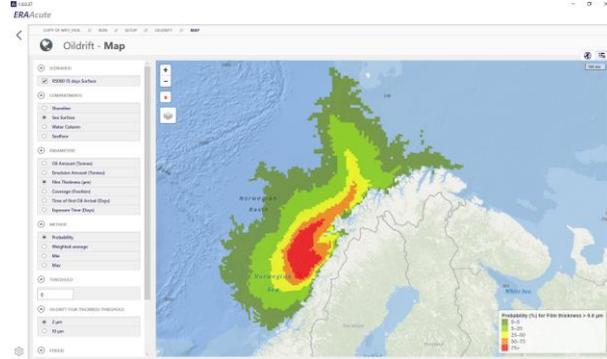


Figure 26. Column plots (top) and box plots (bottom) comparing the exposure time above the threshold thickness (T) for the six scenarios each represented with 237 simulations. The column plot shows the mean values while the box plot illustrates the minimum, first quartile, median (typical value), third quartile, and maximum for the 237 simulations. The whisker length is set at 1.5 times the inter-quartile range (IQR), with black rings showing outliers, including minimum and maximum values.

Film thickness (>2 μm)



Film thickness (>10 μm)

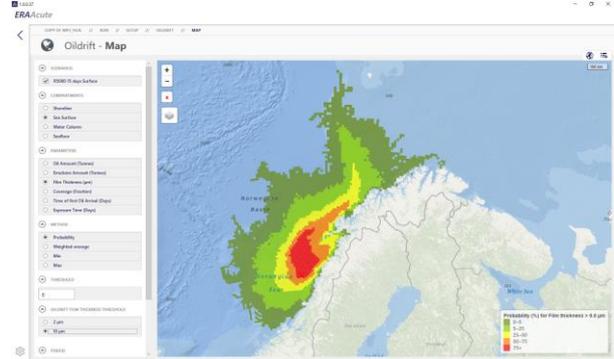
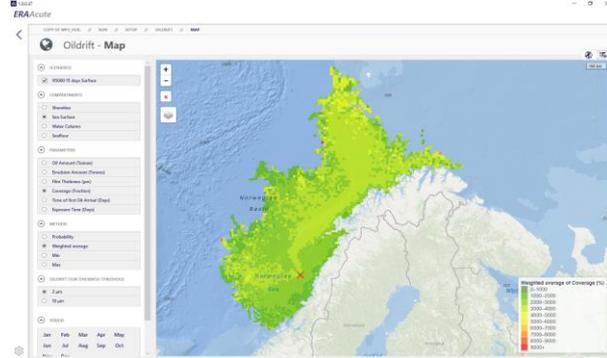


Figure 27. Statistical maps constructed from the stochastic oil drift simulations illustrating the number and probability of grid cells above a threshold thickness of 2 μm (left) and 10 μm (right). Note that the legend does not reflect the threshold thickness (constructed with the ERA Acute Tool v. 1.0.0.37).

Coverage (>2 μm)



Coverage (>10 μm)

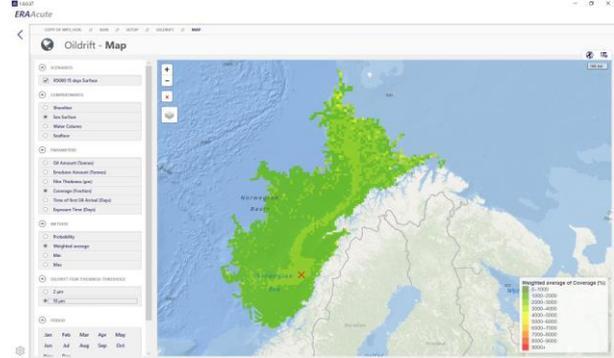
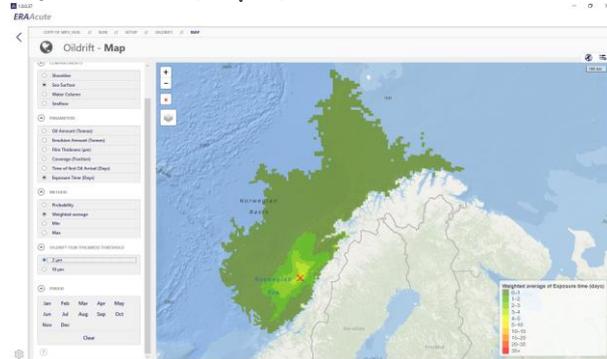


Figure 28. Statistical maps constructed from the stochastic oil drift simulations for all 237 simulations illustrating the mean coverage above a threshold thickness of 2 μm (left) and 10 μm (right). Note that the legend shows two extra zeros (constructed with the ERA Acute Tool v. 1.0.0.37).

Exposure time (>2 μm)



Exposure time (>10 μm)

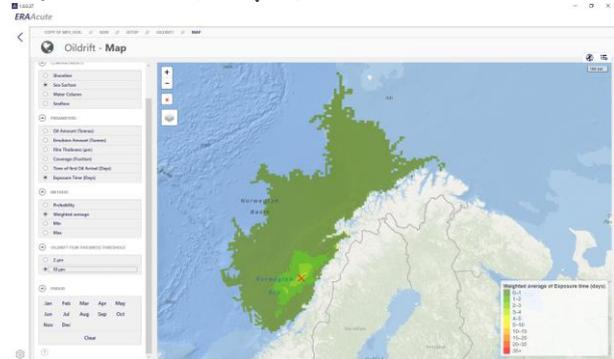


Figure 29. Statistical maps constructed from the stochastic oil drift simulations for all 237 simulations illustrating the mean exposure time above a threshold thickness of 2 μm (left) and 10 μm (right) (constructed with the ERA Acute Tool v. 1.0.0.37).

Effect on impact: A summary of the effect of different thickness threshold on impact (population loss) is summarized in Table 7 and illustrated in Figure 30 to Figure 35. Table 7 presents measures of central tendency (mean) and variability (standard deviation and the 2.5 and 97.5 percentiles) of impact estimated from stochastic oil drift simulations valid for March, April and May ($n = 120$) using equation 2.2 and the individual vulnerability factors in Table 2. The result of the Tukey's range test is presented in the right panel of the table. It shows the p-values for comparison of the mean impact estimated from simulations with different threshold thickness. For example, T04 vs. T06 shows that the mean impact of Atlantic puffin estimated with a threshold thickness of 4 μm (T04) is statistically significantly different from the mean impact estimated with a threshold thickness of 6 μm (T06) at a 5% significance level ($p = 0.0458$).

The estimated impact for all VECs decreases with increasing oil film thickness threshold. The mean impact estimated with a threshold thickness of 2 μm is on average 2.3 times higher than the mean impact estimated with a threshold thickness of 10 μm , ranging from 1.9 (Atlantic puffin, coastal dataset and grey seal) to 2.9 (black-legged kittiwake). As for the oil drift statistics, the difference in the estimated mean impact for 2 and 10 μm is statically significant for all VECs at a 5% significance level. The effect of lowering the threshold thickness from 10 to 8 μm is not statistically significant for any of the species.

In this test, the VECs distributed along the coast are less sensitive to lowering the threshold thickness than the VECs distributed on the open sea. The threshold must be lowered from 10 to 4 μm or 2 μm (grey seal) to obtain a statistically significant effect for the VECs exhibiting a coastal distribution.

In summary: The results show that that the effect of lowering the lethal oil film threshold thickness from 10 to 2 micrometres increases the geographical extent of potentially harmful area (i.e. oil spills will have higher probability of reaching areas that would not be reached using a higher T), the probability that a given area will be affected by harmful oil and the size of the environmental damage (population loss, as well as recovery time and the resource damage factor).

The main findings are:

1. All endpoints investigated are negatively correlated with the oil film threshold thickness (i.e. when increasing the threshold, the endpoints decreases).
2. The effect of lowering the film thickness threshold from 2 to 10 μm has a significant effect on the oil drift statistics and the estimated environmental damage for wildlife in the sea surface compartment.
3. The effect of lowering the threshold from 10 to 8 μm , and partly to 6 μm has smaller effect

Although the results are based on a limited dataset (237 simulations pr. scenario/oil film thickness threshold) it is believed that the general trend demonstrated in this test is valid for a broader range of oil spills (rates, durations, oil types and geographical locations).

Table 7. Percentage population loss for different threshold thicknesses estimated from stochastic oil drift simulations valid for March, April and May (n = 120). The results are based on the individual vulnerability factors (low, medium and high) for the species wildlife group. The result from the Tukey's range test is presented with colour codes indicating statistical effect at a 5% significance level.

Resource	Threshold	Impact (Nlet-2)				Tukey's range test				
		Mean	SD	P _{2.5}	P _{97.5}	T02	T04	T06	T08	T10
Atlantic puffin (WG1) Open Sea Dataset	T00	19.3%	12.4%	3.2%	42.8%	0.0000	0.0000	0.0000	0.0000	0.0000
	T02	10.3%	7.1%	1.4%	25.1%	-	0.0000	0.0000	0.0000	0.0000
	T04	6.8%	5.1%	0.9%	18.6%	-	-	0.0458	0.0001	0.0000
	T06	5.4%	4.2%	0.7%	16.0%	-	-	-	0.4937	0.0472
	T08	4.5%	3.7%	0.6%	14.1%	-	-	-	-	0.8754
	T10	4.0%	3.3%	0.5%	12.9%	-	-	-	-	-
Black-legged kittiwake (WG2)	T00	3.1%	1.3%	1.3%	5.8%	0.0000	0.0000	0.0000	0.0000	0.0000
	T02	1.5%	0.7%	0.5%	3.1%	-	-	0.0000	0.0000	0.0000
	T04	1.0%	0.5%	0.3%	2.1%	-	-	0.0001	0.0000	0.0000
	T06	0.7%	0.4%	0.2%	1.5%	-	-	-	0.0826	0.0002
	T08	0.6%	0.3%	0.1%	1.3%	-	-	-	-	0.5704
	T10	0.5%	0.3%	0.1%	1.1%	-	-	-	-	-
Pelagic bird with uniform distribution (WG2)	T00	3.4%	1.1%	1.6%	5.8%	0.0000	0.0000	0.0000	0.0000	0.0000
	T02	1.9%	0.6%	0.7%	3.2%	-	0.0000	0.0000	0.0000	0.0000
	T04	1.3%	0.5%	0.4%	2.3%	-	-	0.0000	0.0000	0.0000
	T06	1.1%	0.4%	0.3%	2.0%	-	-	-	0.0110	0.0000
	T08	0.9%	0.4%	0.3%	1.7%	-	-	-	-	0.2673
	T10	0.8%	0.4%	0.2%	1.6%	-	-	-	-	-
Atlantic Puffin (WG1) Coastal dataset	T00	11.8%	11.4%	0.0%	33.9%	0.0000	0.0000	0.0000	0.0000	0.0000
	T02	7.3%	8.1%	0.0%	26.9%	-	0.0295	0.0001	0.0000	0.0000
	T04	5.6%	6.7%	0.0%	22.9%	-	-	0.6147	0.1105	0.0112
	T06	4.8%	6.0%	0.0%	20.8%	-	-	-	0.9262	0.4925
	T08	4.2%	5.6%	0.0%	19.1%	-	-	-	-	0.9700
	T10	3.8%	5.3%	0.0%	17.9%	-	-	-	-	-
Common Eider (WG3)	T00	2.8%	1.9%	0.0%	7.2%	0.0000	0.0000	0.0000	0.0000	0.0000
	T02	1.0%	1.0%	0.0%	3.6%	-	0.0090	0.0000	0.0000	0.0000
	T04	0.7%	0.8%	0.0%	2.8%	-	-	0.6151	0.1153	0.0075
	T06	0.6%	0.7%	0.0%	2.5%	-	-	-	0.9313	0.4173
	T08	0.5%	0.7%	0.0%	2.4%	-	-	-	-	0.9417
	T10	0.4%	0.7%	0.0%	2.3%	-	-	-	-	-
Grey Seal (WG9)	T00	0.5%	0.6%	0.0%	2.2%	0.0000	0.0000	0.0000	0.0000	0.0000
	T02	0.2%	0.2%	0.0%	0.9%	-	0.5300	0.1407	0.0304	0.0073
	T04	0.1%	0.2%	0.0%	0.8%	-	-	0.9763	0.7741	0.4946
	T06	0.1%	0.2%	0.0%	0.7%	-	-	-	0.9926	0.9141
	T08	0.1%	0.2%	0.0%	0.6%	-	-	-	-	0.9980
	T10	0.1%	0.2%	0.0%	0.5%	-	-	-	-	-

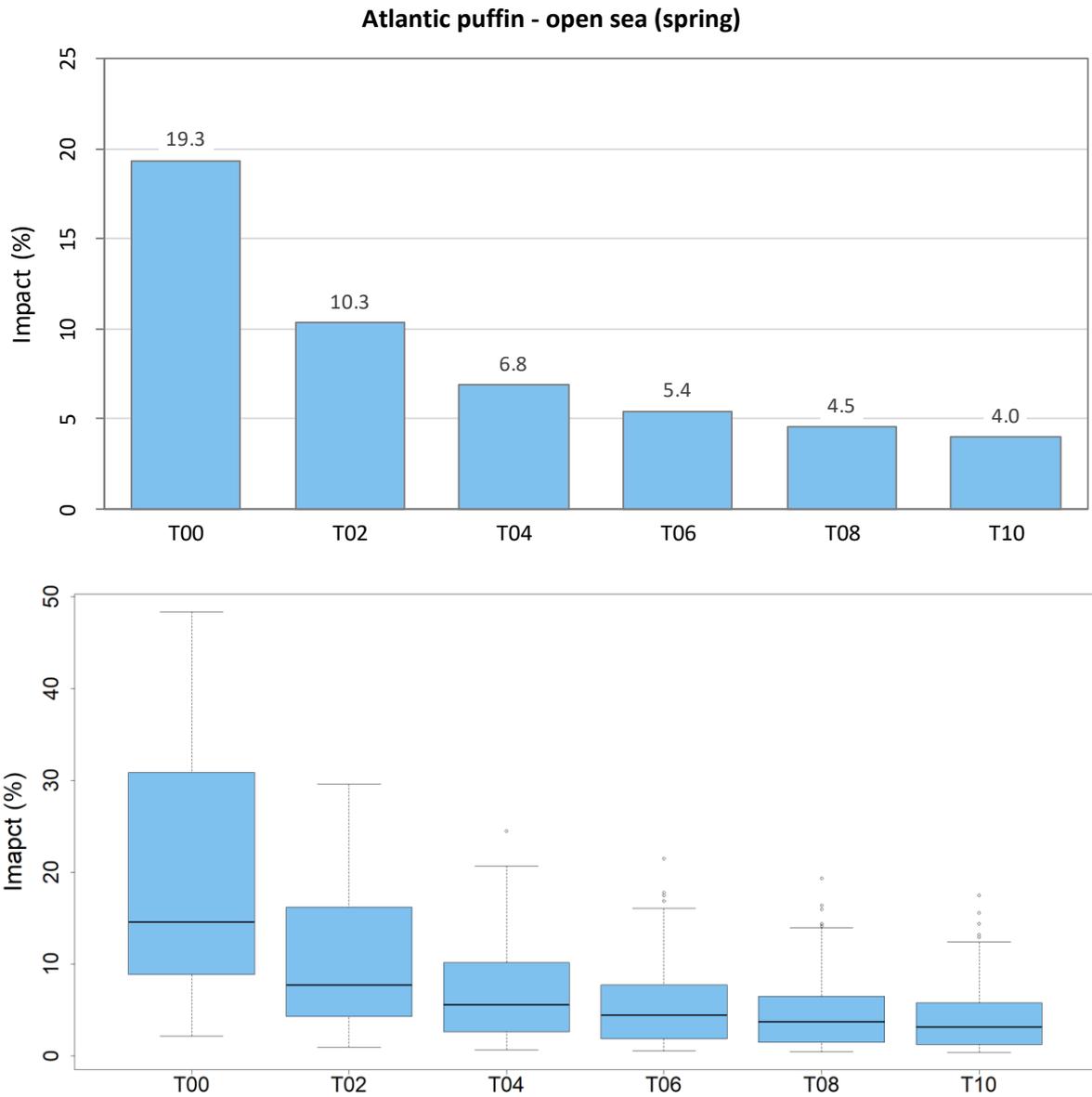


Figure 30. Percentage population loss for different threshold thicknesses estimated from stochastic oil drift simulations valid for March, April and May (n = 120). The bar diagrams (top) shows the mean population loss and the box plot shows the minimum, first quartile, median (typical value), third quartile, and maximum value. The whisker length is set at 1.5 times the inter-quartile range (IQR), with black rings showing outliers, including minimum and maximum values. See Table 7 for details.

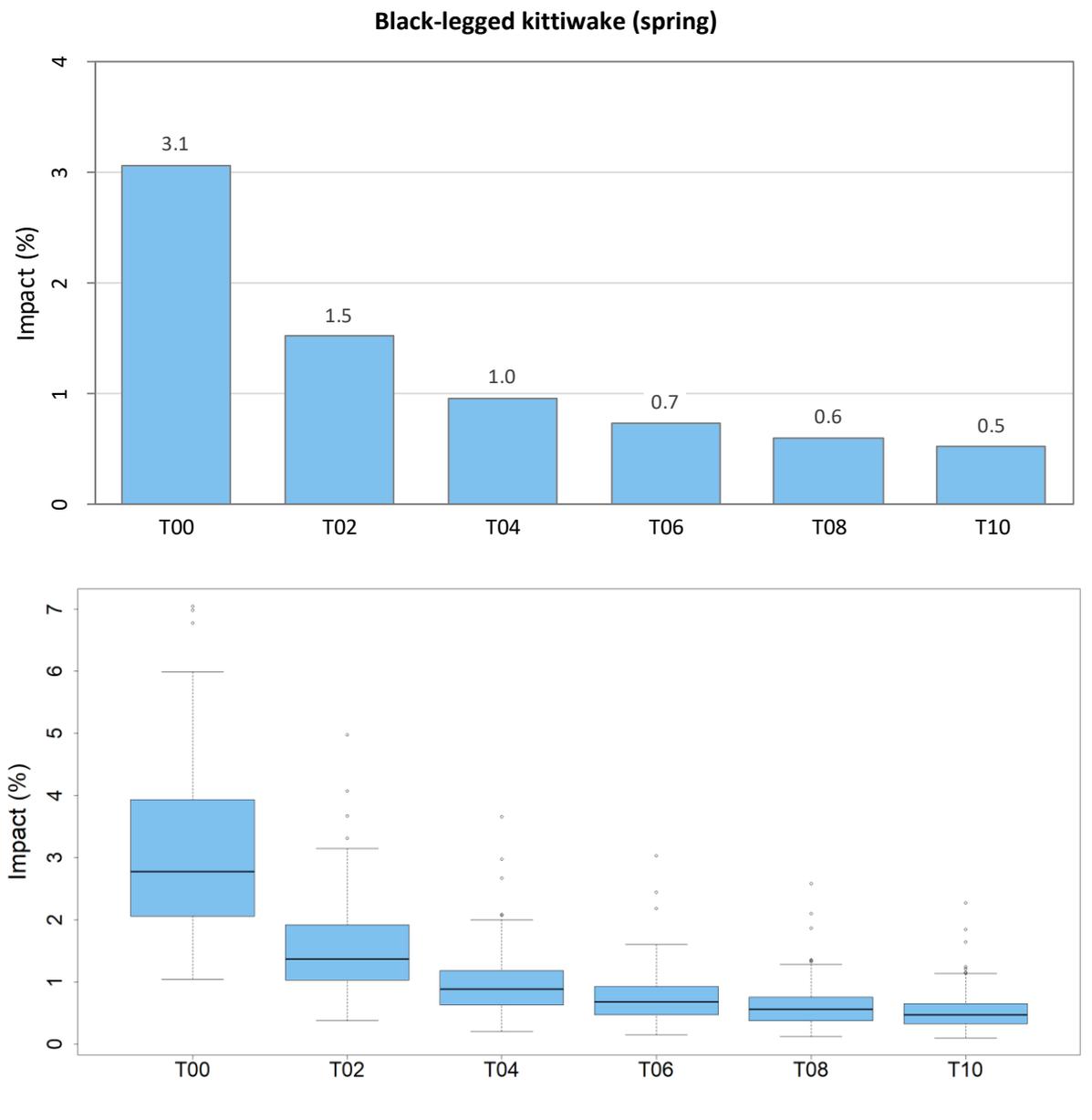


Figure 31. Percentage population loss for different threshold thicknesses estimated from stochastic oil drift simulations valid for March, April and May (n = 120). The bar diagrams (top) shows the mean population loss and the box plot shows the minimum, first quartile, median (typical value), third quartile, and maximum value. The whisker length is set at 1.5 times the inter-quartile range (IQR), with black rings showing outliers, including minimum and maximum values. See Table 7 for details.

Pelagic bird with uniform distribution

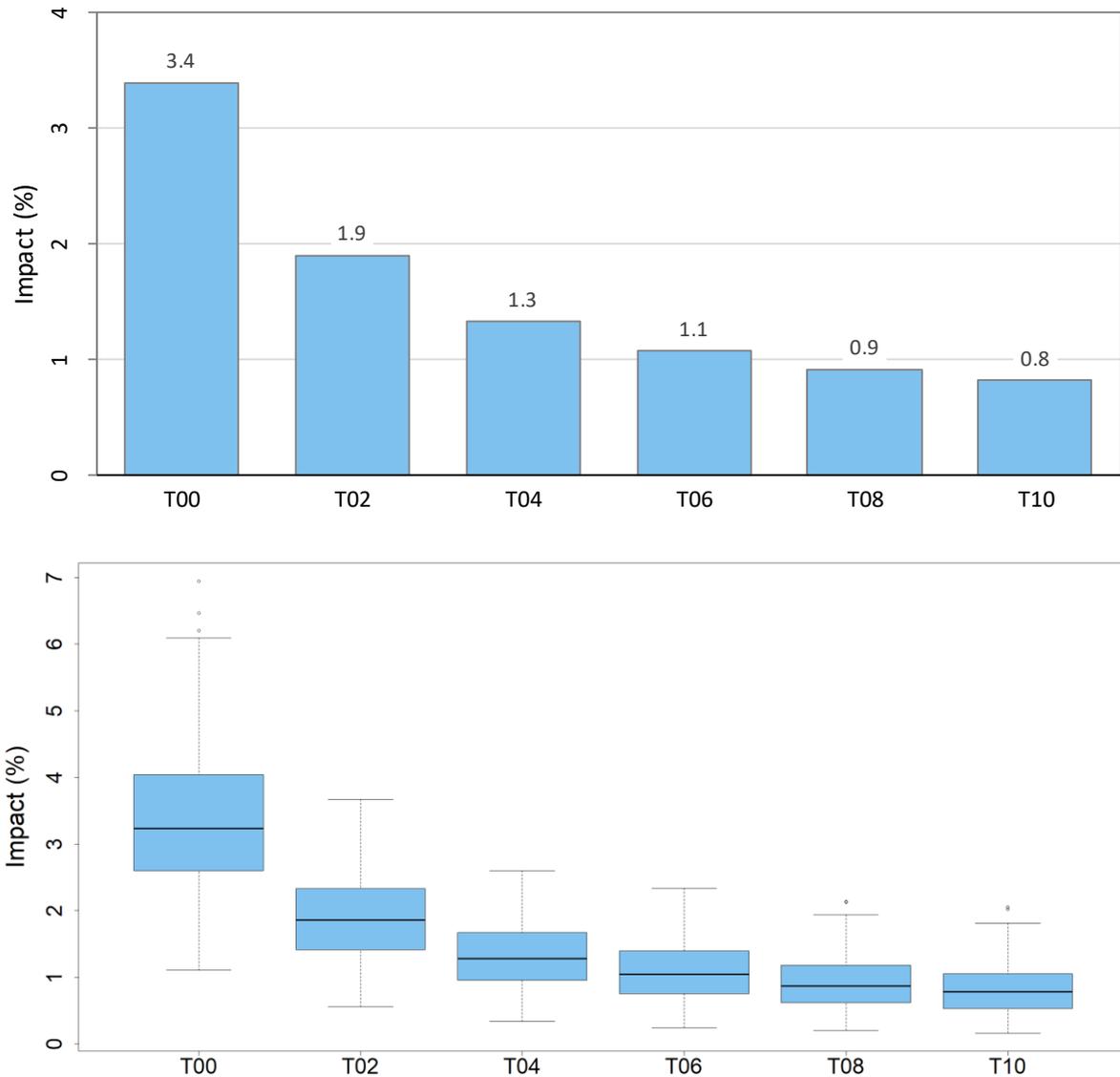


Figure 32. Percentage population loss for different threshold thicknesses estimated from stochastic oil drift simulations valid for March, April and May (n = 120). The bar diagrams (top) shows the mean population loss and the box plot shows the minimum, first quartile, median (typical value), third quartile, and maximum value. The whisker length is set at 1.5 times the inter-quartile range (IQR), with black rings showing outliers, including minimum and maximum values. See Table 7 for details.

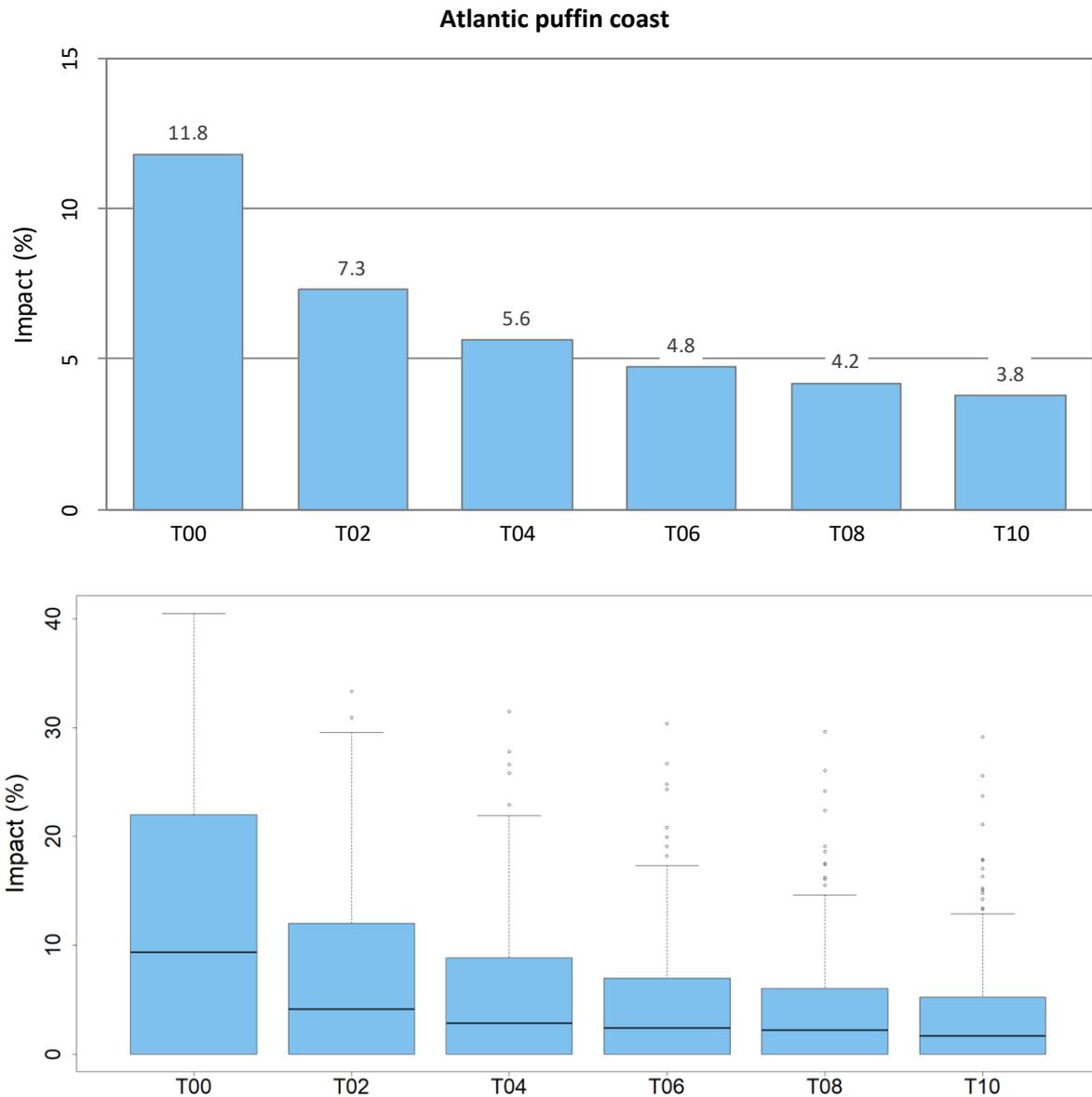


Figure 33. Percentage population loss for different threshold thicknesses estimated from stochastic oil drift simulations valid for March, April and May (n = 120). The bar diagrams (top) shows the mean population loss and the box plot shows the minimum, first quartile, median (typical value), third quartile, and maximum value. The whisker length is set at 1.5 times the inter-quartile range (IQR), with black rings showing outliers, including minimum and maximum values. See Table 7 for details.

Common eider

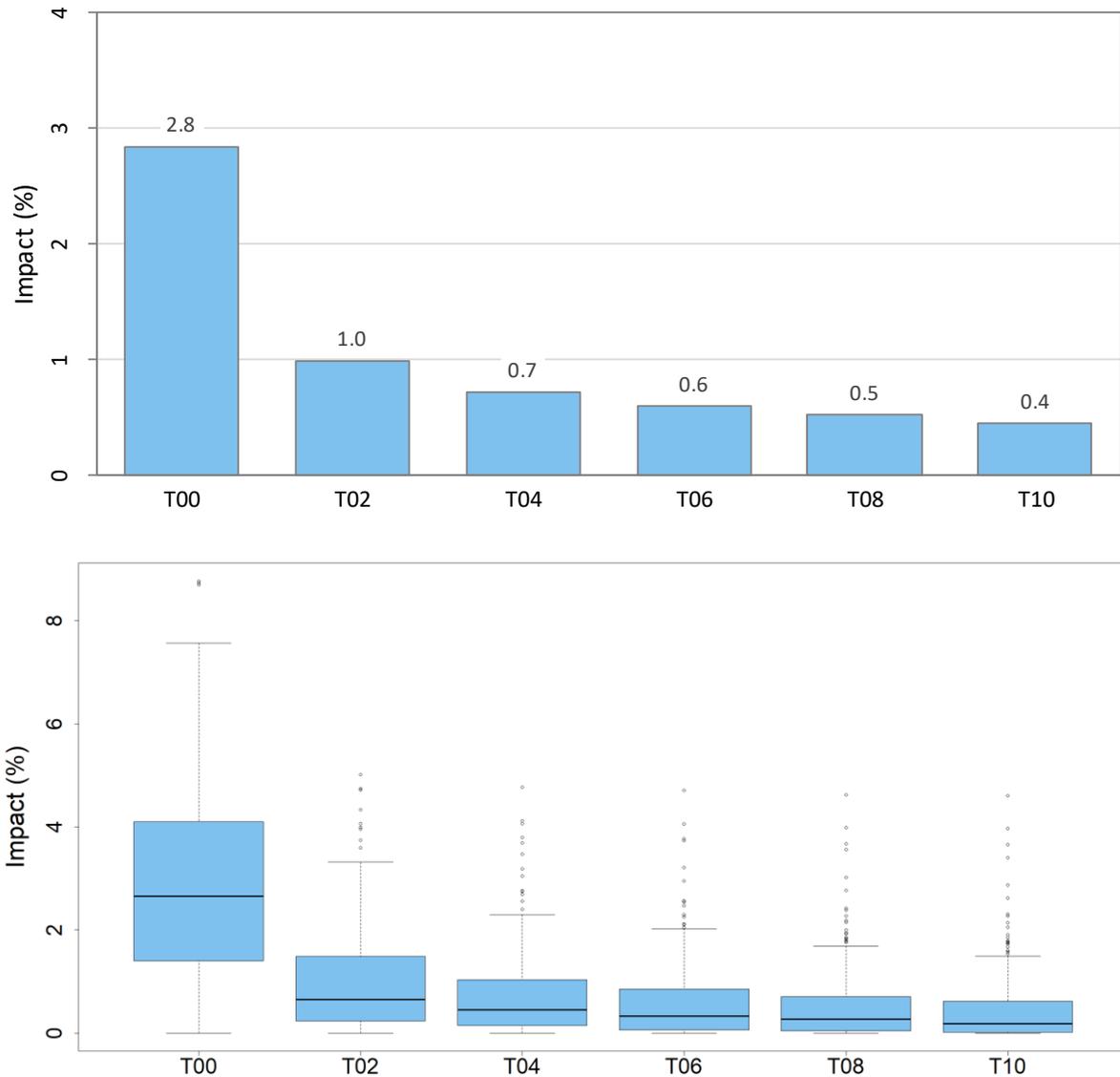


Figure 34. Percentage population loss for different threshold thicknesses estimated from stochastic oil drift simulations valid for March, April and May (n = 120). The bar diagrams (top) shows the mean population loss and the box plot shows the minimum, first quartile, median (typical value), third quartile, and maximum value. The whisker length is set at 1.5 times the inter-quartile range (IQR), with black rings showing outliers, including minimum and maximum values. See Table 7 for details.

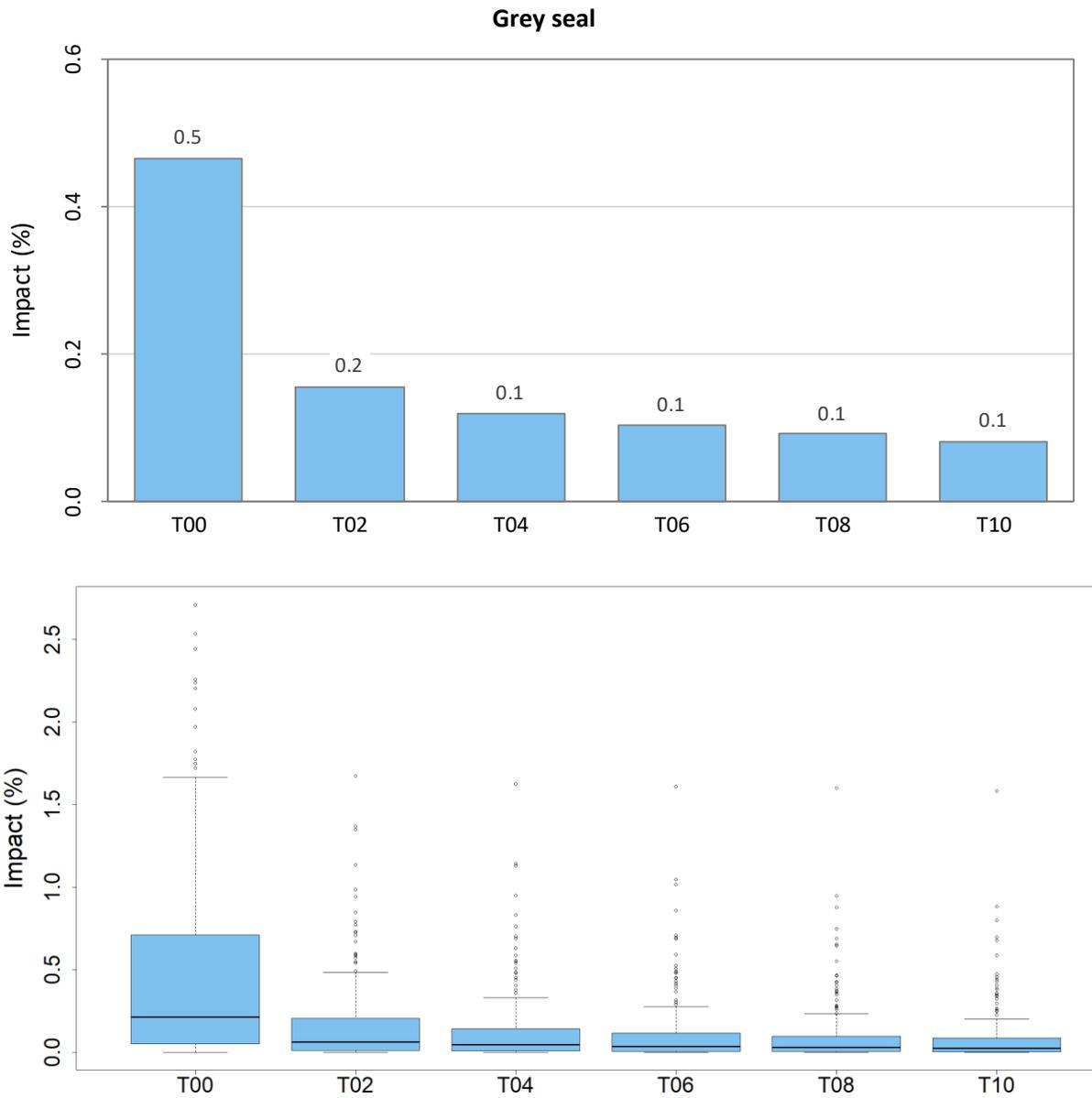


Figure 35. Percentage population loss for different threshold thicknesses estimated from stochastic oil drift simulations valid for March, April and May (n = 120). The bar diagrams (top) shows the mean population loss and the box plot shows the minimum, first quartile, median (typical value), third quartile, and maximum value. The whisker length is set at 1.5 times the inter-quartile range (IQR), with black rings showing outliers, including minimum and maximum values. See Table 7 for details.

3.2 Exposure time

The exposure time (T_{exp}) is a measure of how long oil with oil film thickness above the pre-defined threshold level has been in a grid cell (cf. Box1). The exposure time is estimated from the oil drift model and is implemented in impact equation 2.2 to incorporate the observation that an area exposed for oil contamination for a long period (or many times) will on average be more hazardous for surface VECs such as seabirds than if the same area was exposed for a short period.

Compared to the impact equation without exposure time the mortality increases in cells exposed for oil above the lethal thickness for more than one day and decreases if the cell is exposed for harmful oil for a shorter period, i.e.:

- For $T_{exp} = 1$ day, both equations will give identical impact
- For $T_{exp} < 1$ day, equation 2.2 will result in lower impact than equation 2.1
- For $T_{exp} > 1$ day, equation 2.2 will result in higher impact than equation 2.1

A tipping point of 1 day is selected arbitrary.

Equation 2.2 yields an exponential impact function that gradually approaches an asymptote (plateau). The impact function may be illustrated as an increase in acute mortality or a decrease in the relative abundance in a grid cell over time (Figure 36). The parameters determining how rapidly the processes (mortality or depletion of individuals) occurs is T_{exp} as well as the coverage and the two individual vulnerability factors (p_{beh} and p_{phy}). The number of individuals or population fraction in a cell (N) determines the asymptote or the start points and does not affect the mortality or depletion rate (cf. Figure 6).

How long a grid cell must be exposed to harmful oil contamination to kill $x\%$ of the VECs in the grid cell depends on the individual vulnerability of the VECs (P_{phy} and P_{beh}) and the coverage of harmful oil above the threshold film thickness for the VEC (cf. Figure 7- Figure 19). The number of days it takes to kill $x = 50\%$ and $x = 95\%$ of the individuals in a cell for different wildlife groups and coverages are given in Table 8 and Table 9, respectively. The wildlife groups are sorted by their vulnerability.

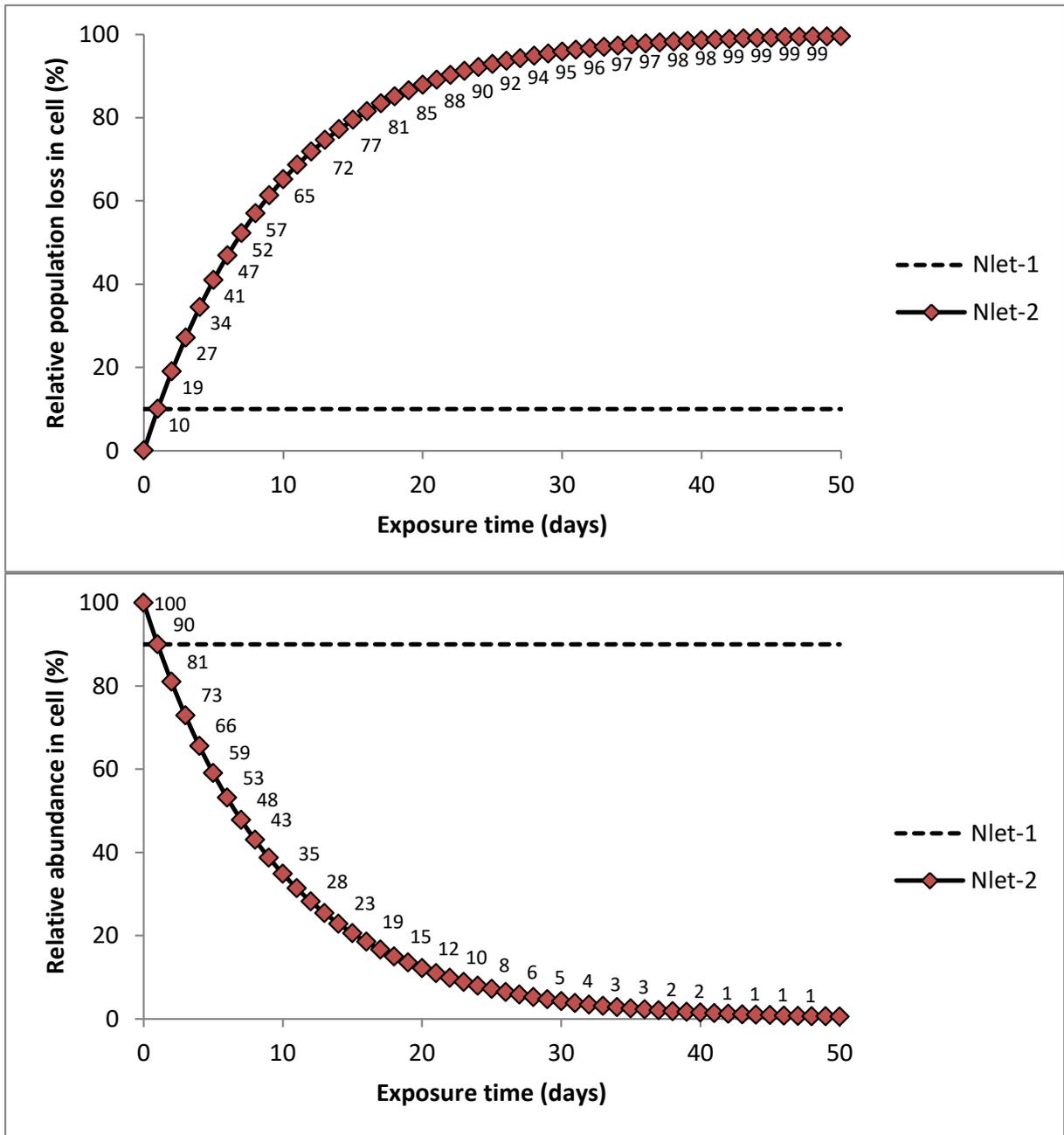


Figure 36. Illustration of effect of exposure time on the relative abundance in the cell (top) and the relative population loss in a cell (bottom).

Table 8. Number of days it takes to kill 50% of the individuals in a grid cell for different coverages above the wildlife groups lethal oil film thickness threshold.

No.	Wildlife groups		Coverage (%)						
			5	10	20	40	60	80	100
1	WG1	Pelagic diving seabirds	19	9.4	4.5	2.1	1.2	0.8	0.6
2	WG12	Aquatic mammals	22	11	5.1	2.4	1.4	1.0	0.7
3	WG3	Coastal diving seabirds	23	11	5.4	2.5	1.5	1.1	0.8
4	WG10	Fur seals	24	12	5.8	2.7	1.7	1.2	0.8
5	WG5	Wetland surface feeding seabirds	32	16	7.7	3.7	2.3	1.6	1.2
6	WG2	Pelagic surface foraging seabirds	34	17	8.2	3.9	2.5	1.8	1.3
7	WG6	Wading seabirds	44	22	11	5.1	3.3	2.4	1.8
8	WG4	Coastal surface feeding seabirds	54	27	13	6.4	4.1	3.0	2.3
9	WG11	Sea cows	329	164	82	41	27	20	16
10	WG13	Sea turtles	466	233	116	58	39	29	23
11	WG9	True seals, walruses and sea lions	550	275	137	68	45	34	27
12	WG8	Toothed whales	2888	1444	722	361	240	180	144
13	WG7	Baleen whales	6,539	3,269	1,634	817	545	408	327

Table 9. Number of days it takes to kill 95% of the individuals in a grid cell for different coverages above the wildlife groups lethal oil film thickness threshold.

No.	Wildlife groups		Coverage (%)						
			5	10	20	40	60	80	100
1	WG1	Pelagic diving seabirds	83	41	20	9.0	5.4	3.6	2.4
2	WG12	Aquatic mammals	93	46	22	10	6.3	4.2	3.0
3	WG3	Coastal diving seabirds	98	48	23	11	6.7	4.5	3.2
4	WG10	Fur seals	105	52	25	12	7.3	5.0	3.6
5	WG5	Wetland surface feeding seabirds	137	68	33	16	10	7.1	5.3
6	WG2	Pelagic surface foraging seabirds	146	72	35	17	11	7.7	5.8
7	WG6	Wading seabirds	189	94	46	22	14	10	7.9
8	WG4	Coastal surface feeding seabirds	231	115	57	28	18	13	10
9	WG11	Sea cows	1,420	709	354	176	117	87	70
10	WG13	Sea turtles	2,016	1,007	503	251	167	125	99
11	WG9	True seals, walruses and sea lions	2,376	1,187	593	296	197	147	117
12	WG8	Toothed whales	12,481	6,240	3,119	1,559	1,039	779	623
13	WG7	Baleen whales	28,260	14,129	7,064	3,531	2,354	1,765	1,412

Which formula does best in comparison with field data?

In the field validation study both equations was used to estimate impact on seabirds, true seals, toothed whales, baleen whales, aquatic mammals and sea turtles (cf. Bjørgesæter et al., 2018 for details). The oil drift parameters used in the calculations are derived from stochastic oil drift simulations in OSCAR v.8.01 and the Python script pysemble v.3. For seabirds, sea turtles, toothed and baleen whales impact was in addition estimated from oil drift data constructed from satellite data derived during the Natural Resource Damage Assessment (NRDA) for the Deepwater Horizon oil spill. The estimated impact from the two equations has been compared with performance boundaries constructed from the field estimates during the NRDA process and from selected peer-reviewed literature for the Exxon Valdez Oil Spill and the Deepwater Horizon Oil Spill.

The overall results are presented in Table 10. In conclusion, the equation which includes the exposure time performs best according to the impact estimated from various field estimates. The results from the field validation study and the MIRA comparison (Brude et al., 2017) supports that it is important to include the exposure time in an impact model for the sea surface. It should be noted that the results in Table 10 is based on input parameters from ERA Acute phase 3, which have not yet been subject to calibration due delays in the project.

Table 10. Overall classification of the estimated impacts for all VECs investigated, calculated from both modelled- and field oil drift data according to the performance boundaries.

VEC Group	N _{Net-1} (Eq. 2.1)					N _{Net-2} (Eq. 2.2)				
	T low	L low	Within	L high	T high	T low	L low	Within	L high	T high
Seabirds	0%	17%	83%	0%	0%	0%	5%	76%	18%	1%
Seals	99%	1%	0%	0%	0%	35%	37%	17%	6%	5%
Whales	100%	0%	0%	0%	0%	82%	15%	3%	0%	0%
Aquatic mammals	0%	0%	100%	0%	0%	0%	0%	100%	0%	0%
Sea turtles	100%	0%	0%	0%	0%	43%	3%	8%	1%	45%

Investigation of the properties of Equation 2.2 with use of the satellite oil drift data may indicate that the effect of the exposure time may be given too much weight. An illustration of the relationship between impacts estimated with the two equations for seabirds, whales and sea turtles calculated from field oil drift data is given in Figure 37. The figures show the impact per grid cell from one Monte Carlo Simulation using the most likely value (mode) for the individual vulnerability factors. The resource data is VEC-D2 for seabirds, common bottlenose dolphin and the loggerhead sea turtle. The left panels show the relationship between impacts calculated with Eq. 4.1 (N_{let-1}) and Eq. 4.2 (N_{let-2}) and the two others the relationship between abundance in the cell and the estimated impact.

The slope of the curves for the left panels illustrates the effect of the exposure time. In this example it is 4.9 (seabird), 21.9 (dolphin) and 21.2 (turtle), meaning that e.g. a population loss of 100 seabirds with Eq. 2.1 (N_{let-1}) is expected to give a loss of 490 seabirds using Eq. 2.2 (N_{let-2}). The middle and right panels show the estimated mortality for various abundances of the VEC in a grid cell. For ca. 1000 seabirds in a grid cell, the estimated impact will be 96 individuals (range 0.3-302) with Eq. 2.1 (middle panel) and 504 with Eq. 2.2 (range 0.3-976) (right panel). Similarly, with 40-50 common bottlenose dolphins in a grid cell, the estimated impact will be 0.05 (range 0.00-0.15) individuals with Eq. 2.1 and 0.82 (0.00-6.46) with Eq. 2.2. Finally, for 150-200 sea turtles in a grid cell, the

estimated impact will be 2.2 (range 0.0-3.5) individuals with Eq. 2.1 and 46.5 (range 0.0-118) with Eq. 2.2.

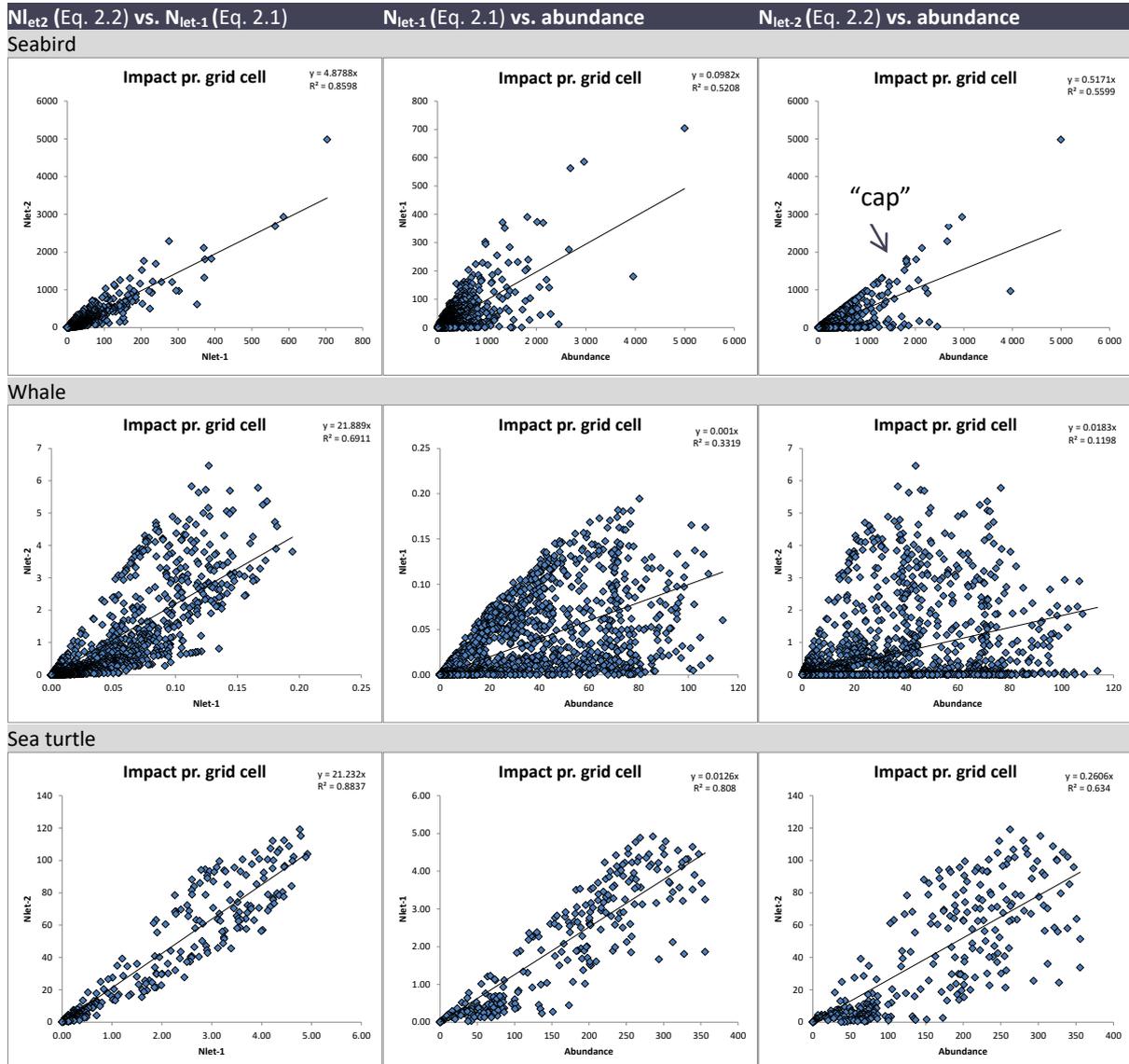


Figure 37. Relationship between impacts estimated for with (Nlet-2) and without exposure time (Nlet-1); Nlet-2 versus Nlet-1 (left column), Nlet-1 vs. abundance (middle column) and Nlet-2 vs. abundance (right column) for seabirds (top row), whales (middle row) and sea turtles (bottom row). See text for details.

The impact models use oil drift statistics calculated for the whole period of the spill. The equation with exposure time assumes that the VECs have equal density across the grid cell (uniform distribution) and that they remix within the cell each day. Fraser et al. (2006) put noticeably more weight on exposure time than the ERA Acute model when estimating the number of seabirds killed by exposure to produced water. Similar, Haney et al. (2014a; 2014b) included exposure time by multiplying the impact of the daily slick areas with the number of days with observed oil slick within 40 km of the coast (95 days) or in offshore areas (103 days) (cf. Equation 5 and 3 in Haney et al. 2014a and 2014b, respectively). In offshore areas it was assumed that it was most likely that it took

4 days to replenish the bird density above the oil slicks (i.e. the total mortality = daily mortality × ¼ × 103 days). Taken into consideration (1) that the mean cumulative daily slick area used by Haney is approx. 3.2 times smaller than the mean cumulative total oil slick used in ERA Acute and (2) that the mean exposure time is 12 days in the cumulative oil slick used in ERA Acute, exposure time is weighed as less important in the ERA Acute impact model.

Based on the above discussion and given the fact that the oil drift model OSCAR that will be used together with ERA Acute in Phase 5 predicts considerably shorter exposure time than the examples above (i.e. field oil drift data from DHOS), it is concluded that it is not necessary to modify the importance of the exposure time in the impact equation.

Modification of the importance of exposure time

Although it is concluded above that the exposure time weighted satisfactorily in Equation 2.2 a short review of possible methods to change the importance of the exposure time is included. In Equation 2.2 it is assumed that wildlife is distributed in equal density across each grid cell and that they remix within each grid cell each day (or each time step). For each day with harmful oil in the cell, individuals oiled above a threshold thickness are assumed to die. The remaining individuals may be oiled in subsequent days if oil is still present on the water surface (i.e. if $T_{exp} > 1$). This means that in practice all individuals in the cell will eventually be killed given long enough exposure (cf. Figure 38 – the black curves).

One possible refinement of Equation 2.2 is to use the coverage in the cell to adjust the probability of being oiled in subsequent days (i.e. the slope of the curve), as illustrated in Equation 3.1. The effect is illustrated in Figure 38 (red dots) for pelagic birds for a coverage of 10 and 25% respectively.

Another, simpler method is to use a factor, i.e. replace the Coverage with a number between 0-1 to reduce its importance and above 1 to increase its importance. As mentioned above, the results from the WP2 studies do not imply that this modification should be performed given that the input data to the ERA Acute model in foreseeable future be from the oil drift model OSCAR.

$$N_{let-2} = \sum_{i=1}^n N_i - (1 - p_{beh} \times Cov_{iT} \times p_{phyT})^{T_{expiT} \times Cov_{iT}} \times N_i \quad 3.1$$

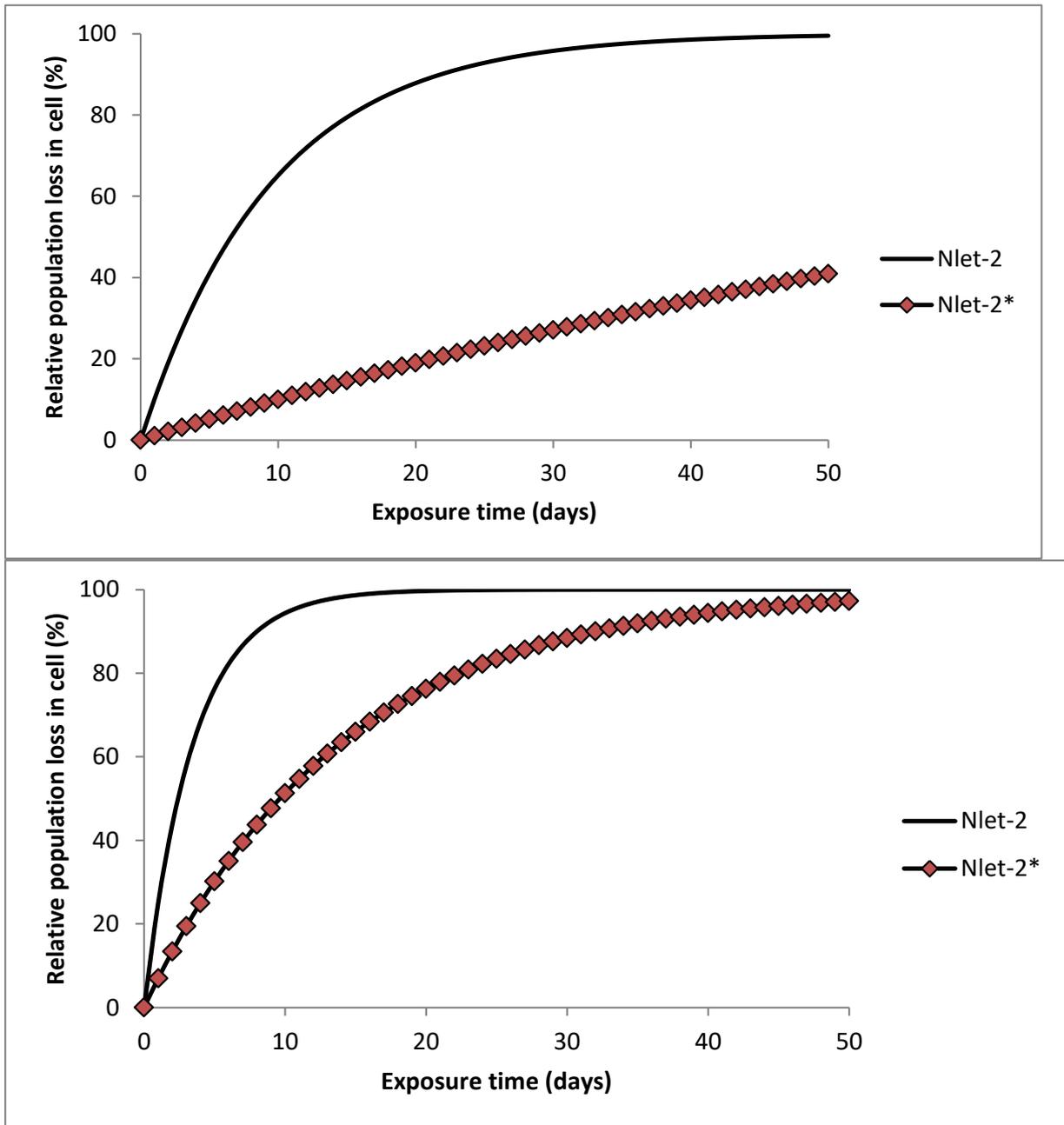


Figure 38. Illustration of the effect of weighting the effect of exposure time (Texp) with the percentage coverage of harmful oil in the grid cell. Upper: Coverage is equal to 10%. Bottom: Coverage is equal to 25%

4 The population model

A logistic discrete population model is used to estimate the restitution time and the recovery damage factor for surface VECs in ERA Acute. The model estimates the population size in generation $t+1$ as a function of the population size (numbers of individuals or fraction) in the previous generation. The model is given by the following equation:

$$N_{t+1} = \frac{N_t R}{1 + (aN_t)^b} \quad 4.1$$

where R is the fundamental net reproductive rate, a is $(R-1)/K$, where K is the carrying capacity of the population and b is a factor determining the strength of the density dependency in the population. N_t is the size of the population at time t and is derived from the impact equations (the population size before the accident – N_{let-1} or N_{let-2}).

To run the model the user needs to define these parameters for the relevant VECs (Table 11). The fundamental population growth rates (R) have previously been derived for seven wildlife groups based on a literature study, basic life history traits (parameters) and an R-Calculator (cf. Bjørgesæter and Damsgaard Jensen, 2015). The R 's for seven groups vary between 1.03 to 1.10, representing the large variation in life history traits for VECs in the surface compartment. For the other population model parameters needed to run the model, standard (default) values are given in look-up tables.

Table 11. Generic look-up table for R-values for eight wild life groups (VEC groups) and recommended standard values for the b and TLR parameter.

No.	Wildlife group	Example of species	Example of families	R	b	TLR
1	Albatross and skuas	Albatross (Southern royal, Grey-headed Antipodean, Northern royal), skua (brown, great), Northern fulmar	Diomedidae, Stercorariidae, Procellariidae	1.05	1	0.95
2	Auks, petrels and shearwaters	Auks (razorbill, common guillemot, Atlantic puffin), petrels (black, white-chinned, Chatham), shearwaters (Bullers, flesh-footed), Black-legged kittiwake	Alcidae, Procellariidae	1.10	1	0.95
3	Gannets, penguins, gulls and terns	Gannets (northern, masked Australasian), penguins (Snares crested, Southern rockhopper, Fiordland crested), Gulls (black-backed, lesser black-backed, little) and terns (common white, common, sandwich, Caspian)	Sulidae, Spheniscidae	1.15	1	0.95
4	Cormorants, shags, divers, ducks and goose	Cormorant (great), shags (European, Campbell Island, spotted, Auckland Island), divers (red throated), ducks (common eider, common scoter) and goose (barnacle, snow, Bewicks swan)	Anatidae, Gaviidae,	1.20	1	0.95
5	True seals, sea lions and fur seals, baleen whales	Grey seal, harbour seal, ringed seal, Antarctic fur seal, subantarctic fur seal, blue, humpback and southern right whales	Balaenopteridae	1.13	1	0.95
6	Walrus, aquatic mammals	Walrus, polar bear, Eurasia otter, sea otters	-	1.06	1	0.95
7	Toothed whales, sea cows, sea turtles	Bottlenose dolphin, killer whale, harbour porpoise, Florida manatee, sea turtles	Delphinidae, Phocoenidae, Trichechidae, Dugongidae	1.03	1	0.95

An illustration of the model is presented in Figure 39. A detailed description of the properties and assumptions of the model is given in Bjørgesæter and Damsgaard Jensen (2015). The restitution time (t_{res}) is defined as the time from restitution starts until the time when the affected population is estimated to be back at a pre-defined threshold level of the non-affected population. A stable baseline population size in the non-affected population is assumed, i.e. a population size equal to the population size before the accident.

The recovery damage factor (RDF) is expressed as *population loss years* and is the summed differences between the “two projections” (i.e. the population growth curve and a steady state fixed population size). It is implemented in the ERA Acute Calculator with the following formula:

$$RDF = 0.5 \times t_{imp}(1 - N_0) + t_{lag} \times (1 - N_0) + \int_{t_{lag}}^{t_{res}} 1 - N(t)dt \quad 4.2$$

Where t_{imp} is the impact time (default 1 year), t_{lag} is the lag-time and t_{res} is the restitution time. N_0 is the population size at $t=0$ (the population size before the accident – population loss).

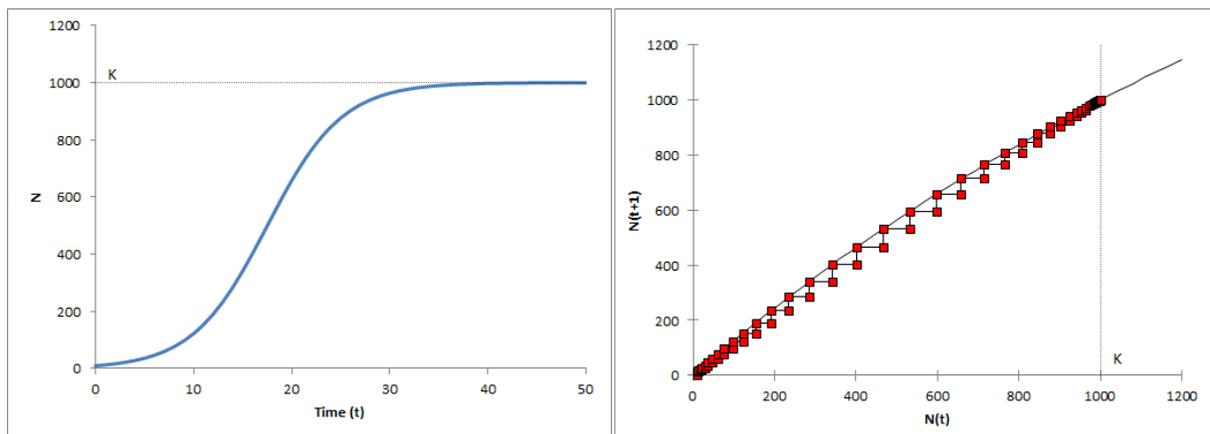


Figure 39. Illustration of the population model in ERA Acute. Note that in nature a population does not typically remain at a steady state continually but instead tends to fluctuate around or below the carrying capacity due to regulating abiotic and biotic effect. In nature small populations relative to the carrying capacity is often observed to increase in number and large populations relative to the carrying capacity is often observed to decline in numbers.

4.1 Uncertainty and sensitivity analysis

The base values and the probability distributions of the model input data used in the deterministic and stochastic uncertainty and sensitivity analyses are presented in Table 12. The base values used in the deterministic analyses are chosen so that the investigated range covers a realistic range of the input data values, except the population loss, which is fixed at 20% in the deterministic analysis. The population model features for different population losses for the different wildlife groups are investigated in Chapter 4.1.3.

Table 12. Model table for the population model for the surface compartment. The endpoints (model output) for the analyses are restitution time (t_{res}) and recovery damage factor (RDF).

Input data	Base value	Parameters		Distribution
		Parameter 1	Parameter 2	
R	1.10	1.03	1.20	Uniform
b	1	0.5	1.5	Uniform
TLR	0.95	0.90	0.99	Uniform
Population loss	20%	Fixed values		-

4.1.1 Deterministic analyses

The endpoints are the restitution time (t_{res}) and the recovery damage factor (RDF). The following parameters are investigated (cf. Table 12):

- TLR = Threshold Level for Recovery
- R = fundamental net reproductive rate
- b = density dependency factor

The analyses are performed using scatter plots. The arrows in selected figures illustrate the effect of selecting a value different than the (default) standard value for the population model parameter. A red arrow illustrates a more conservative choice than using the standard value and a green arrow illustrates a less conservative choice than using the standard value.

4.1.1.1 *The fundamental net reproductive rate (R)*

The restitution time and the resource damage factor (RDF) with varying fundamental net reproductive rates are presented in Figure 40 and Figure 41. The red rings illustrate R-values for selected wildlife groups with examples of characteristic species in the group.

Both the restitution time and the resource damage factor are negatively correlated with R. Both endpoints vary greatly with R, and thus a given population loss will result in considerable variation in restitution time and resource damage factor for the seven wildlife groups, reflecting the large variation in the life history traits of the seven wildlife groups. Long lived species with high annual survival rate, late reproduction debut, few offspring and long parental care, such as the killer whale, will have lower recovery potential than shorter lived species such as the common eider, which has lower annual survival rate, earlier reproduction debut, many offspring and less parental care. Thus, a population loss of e.g. 10% are likely to have a larger negative effect (longer restitution times and higher RDF) on a killer population than a common eider population.

The restitution time and the resource damage factor have an almost perfect positive correlation ($R^2 = 1.00$). In this example (population loss = 20%) an increase of 1 year in restitution time increases the resource damage factor with 0.8%. This relationship will, however, vary with the values of the fixed variables, e.g. an increase of 1 year in restitution time with a population loss of 60% (with the other variables being identical) will for example increase the resource damage factor by 6.1%. These events (singularities) are addressed in the stochastic uncertainty and sensitivity analyses performed in Chapter 4.1.2.

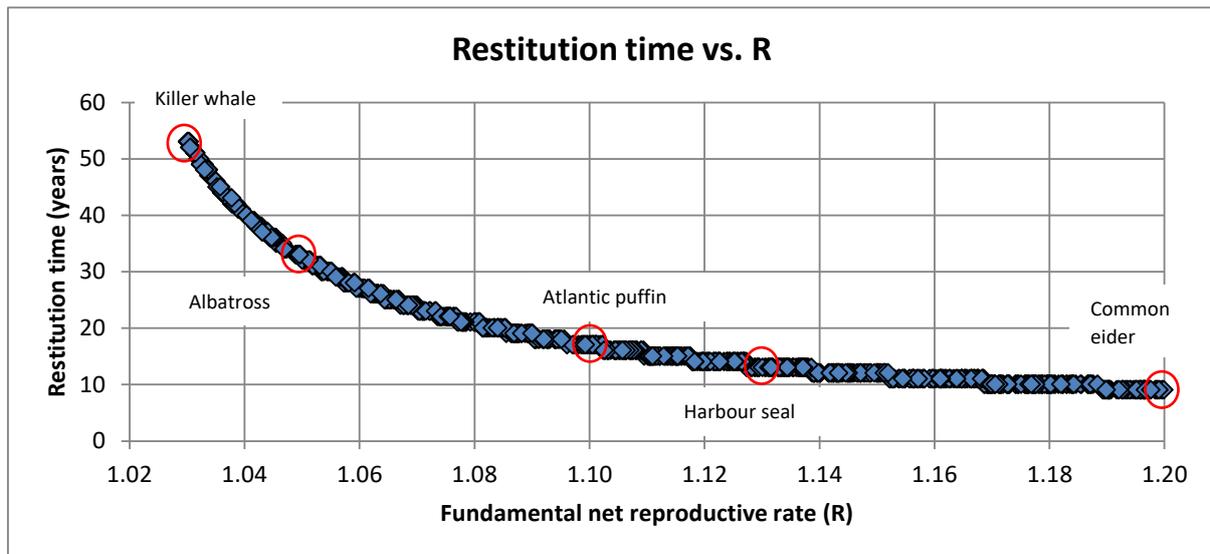


Figure 40. The variation of T_{res} with R for the following fixed variables: population loss = 20%, $b = 1$ and TLR = 0.95.

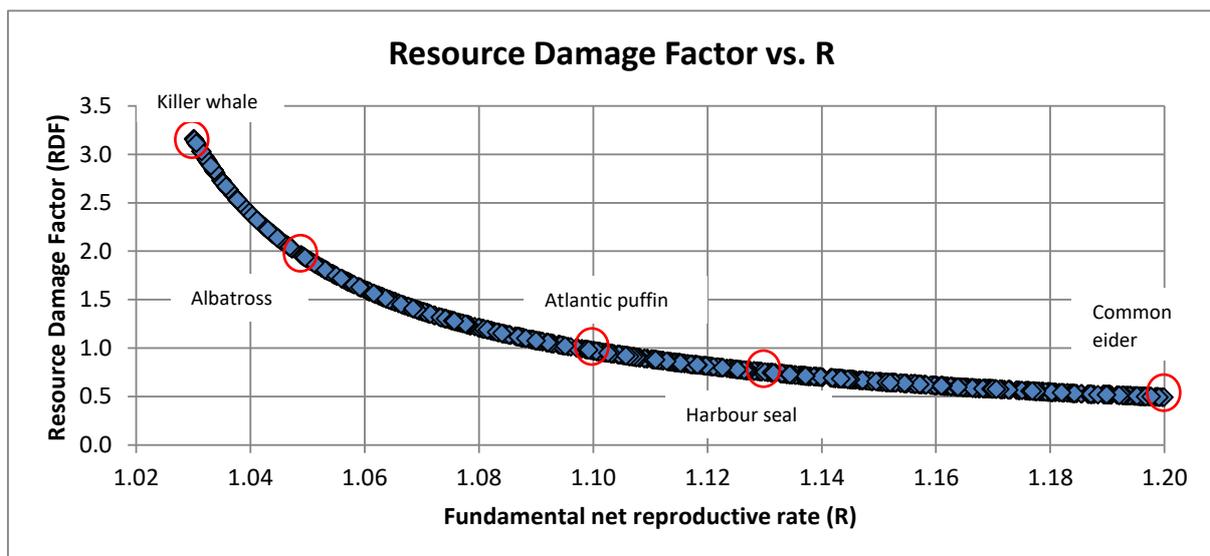


Figure 41. The variation of RDF with R for the following fixed variables: population loss = 20%, $b = 1$ and TLR = 0.95.

4.1.1.2 The density dependency factor (b)

The variable b introduces the possibility to include different types of density dependence in the model. The effects of the b parameter in the model are:

- $b = 1$ keeps the importance of density-dependent processes constant (perfect compensation)
- $b = 0$ removes the importance of density-dependent processes (density independent)
- $b < 1$ increases the importance of density-dependent processes (under compensation)
- $b > 1$ decreases the importance of density-dependent processes (over-compensation)

The range tested for b is between 0.5 and 1.5. The other parameters are held constant at their base values. The restitution time and the resource damage factors from varying the density factor is presented in Figure 42. The red ring illustrates the suggested standard (default) value.

Both endpoints (restitution time and RDF) are negatively correlated with b . Increasing the value of b from its default value decreases the restitution time and the resource damage factor, and decreasing the value increases the restitution time and the resource damage factor. This relationship is valid for $b > 0$. Within the range, the effect is larger when decreasing the value than when increasing the value (cf. the slope of the curves / length of the “steps”). Increasing b from 1.0 to 1.5 decreases the restitution time from 17 to 11 years (and RDF from 0.97 to 0.65), while decreasing b from 1.0 to 0.5 increases the restitution time from 17 to 33 years (and RDF from 0.97 to 1.93). The restitution time and the resource damage factor have almost a perfect positive correlation ($R^2 = 1.00$).

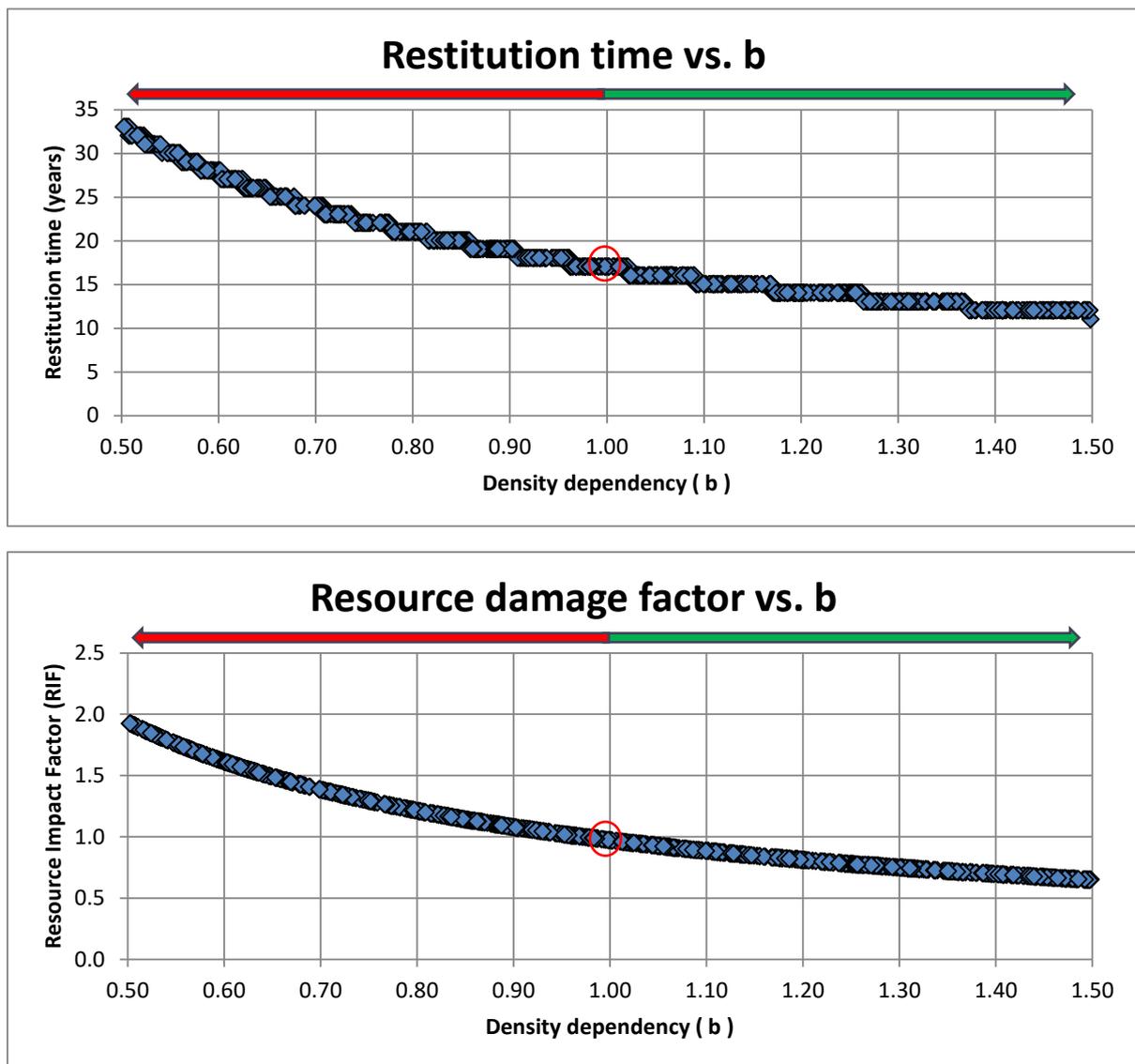


Figure 42. The variation of t_{res} (top) and RDF (bottom) with b for the following fixed variables: population loss = 20%, $R = 1.10$ and $TLR = 0.95$. The red ring illustrates the suggested standard (default) value. The arrows show the effect of selecting a value different than the standard value for the model parameter. A red arrow illustrates a more conservative choice than using the standard value and a green arrow a less conservative choice than using the standard value.

Recommend use of b: According to the pre-request for ERA Acute Phase 3, a standard value should be either “neutral” or “conservative”, with respect to its effect on the endpoint that is modelled. The recommended default value for b is therefore 1 (neutral). The logistic population model performs satisfactorily well compared to the field assessment for VECs affected by the Exxon Valdez Spill. The estimated restitution times from the model were however, outside the set performance boundary ranges when restitution was inhibited by unknown extrinsic factors (high predation, hunting, food shortage, disease etc).

In such cases changing the value of the density dependent factor (b) will improve the model performance. This may be a more robust and biological correct practice than changing the fundamental growth rate (R) of the population, since R is a measure of the growth rate for population living under optimal conditions with no limiting factors (i.e. limiting factors is included in the attributes of the model).

Modelling the effect of extrinsic factors inhibiting the growth of a population requires good knowledge about how the different factors affect the population and a more complex and dynamic population model. For example, the inclusion of predation requires knowledge of the population growth rates of the different relevant predators and their predation rate at different prey densities, as a minimum. A practical solution for standard environmental risk analyses may be to apply the b factor as a measure of the “general health” of the population (“good”, “medium” and “poor”).

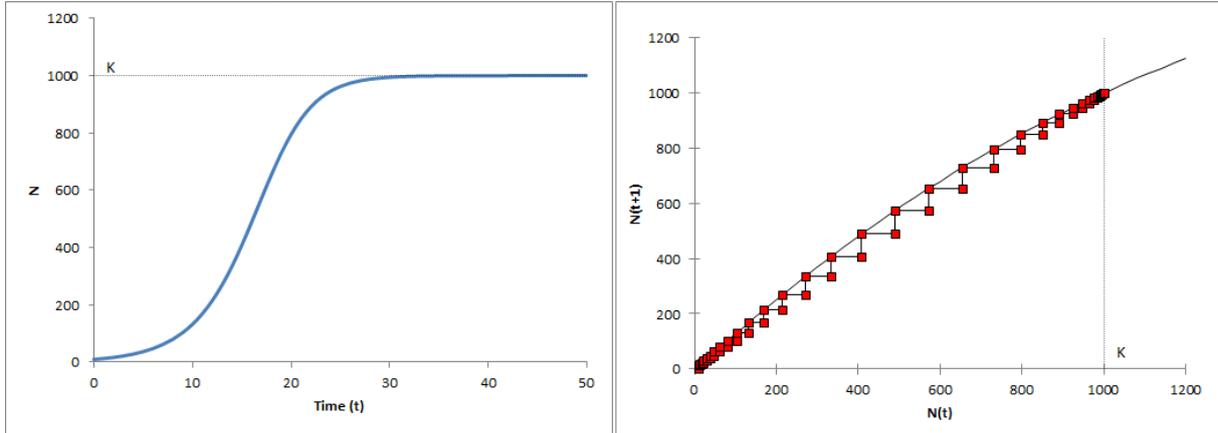
This kind of information requires long-term monitoring but is available and may be provided in the future for several of the seabird populations in Norway.

An example is illustrated in Figure 43, using

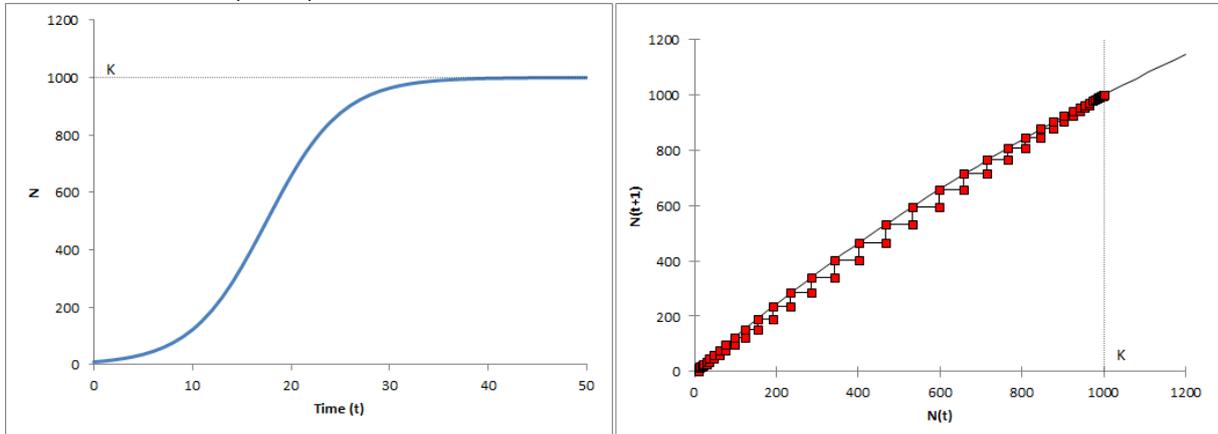
- $b = 1.4$ for “good”
- $b = 1.0$ for “medium”
- $b = 0.7$ for “poor”

This yields a shorter and longer restitution times using the default value of 1. The b values for different health categories must be specific for different populations and e.g. bird colonies.

Health status: good ($b = 1.4$)



Health status: medium ($b = 1.0$)



Health status: poor ($b = 0.7$)

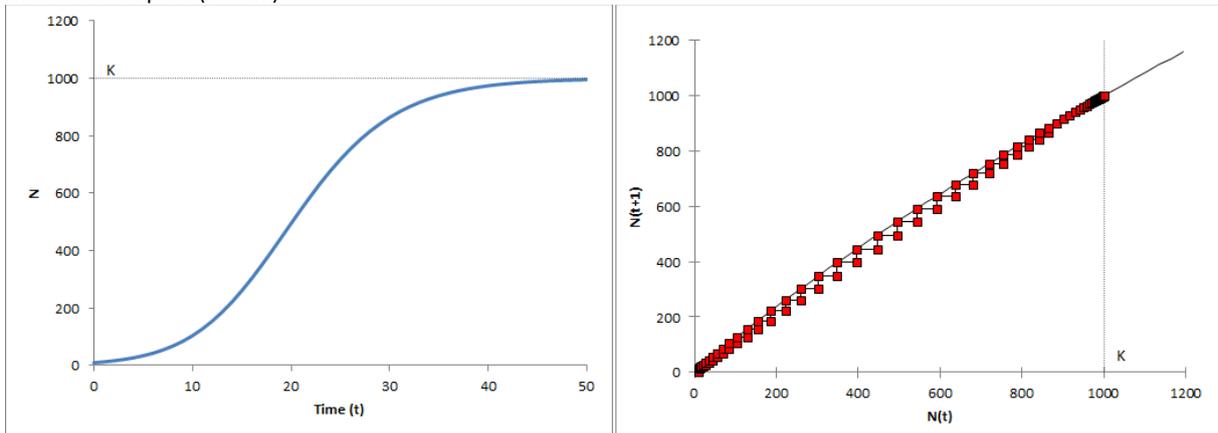


Figure 43. Illustration of the restitution curve (left) and logistic population growth (right) for different values of b , representing different health statuses of the population.

4.1.1.3 The threshold level for recovery (TLR)

The restitution time and the resource damage factor with varying threshold levels for recovery are presented in Figure 44. The red ring illustrates the suggested standard (default) value for TLR. The range tested for TLR is between 0.90 and 0.99. The other parameters are held constant at their base values.

Both endpoints (t_{res} and RDF) are, as expected positively correlated with TLR. Increasing the value of TLR from its standard value increases the restitution time and the resource damage factor, and decreasing the value decreases the restitution time and the resource damage factor.

In contrast to the two model parameters (R and b) there is a marked difference in the effect of high TLRs for the restitution time and for the resource impact factor. The model is a logistic model and the carrying capacity forms an asymptote. Consequently, the population size never comes back to “equilibrium”; it only comes closer and closer. Mathematically this means that the restitution time is infinite for this class of models. Since this has less effect on the area, the RDF is less sensitive to parameters that increase the restitution time than the restitution time itself to these parameters.

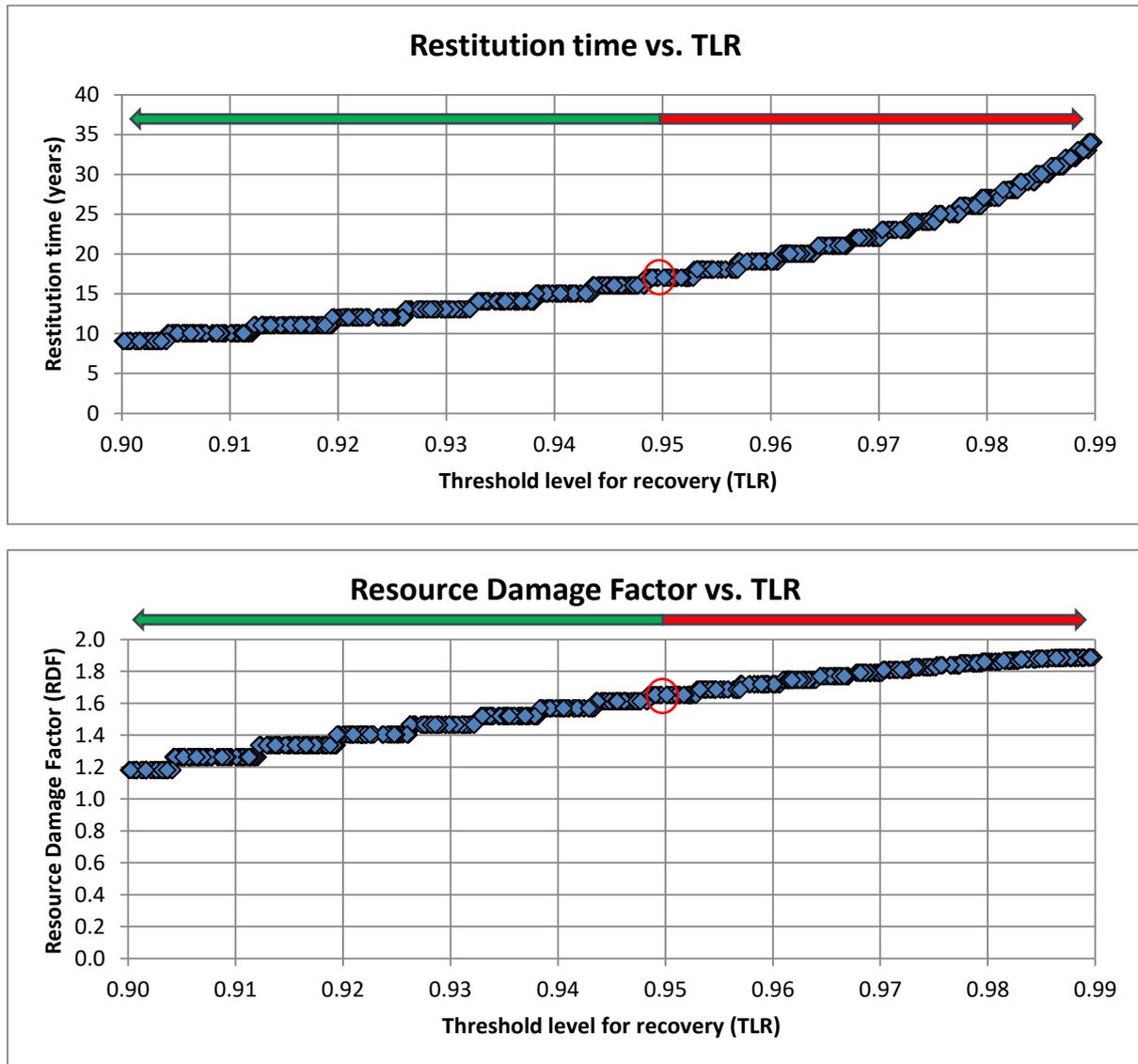


Figure 44. The variation of T_{res} (top) and RDF (bottom) with TLR for the following fixed variables: population loss = 20%, $b = 1$ and $R = 1.10$. The red ring illustrates the suggested standard (default) value. The arrows show the effect of selecting a value different than the standard value for the model parameter. A red arrow illustrates a more conservative choice than using the standard value and a green arrow a less conservative choice than using the standard value.

4.1.2 Stochastic analysis

To quantify the relative importance of the model parameters on the two endpoints (t_{res} and RDF), stochastic uncertainty and sensitivity analyses have been performed based on Monte Carlo Simulation of variation in all three model parameters, i.e. (cf. Table 12):

- R: 1.03 – 1.20
- b: 0.5 – 1.5
- TLR: 0.90-0.99

All three parameters are assigned a uniform probability distribution. The population loss is held constant at 20%.

The results from the Monte Carlo Simulation ($n = 1000$) is presented in Figure 45. Figure 45 shows the relative frequency (probabilities of the possible outcomes) for the two endpoints t_{res} and RDF as a result of the variation in the input variables. The mean restitution time is $21 \pm SD 16$ years, with a subjective 95% confidence interval that range from 6 to 65 years. The mean resource damage factor is 1.94 ± 1.30 with a subjective 95% confidence interval of 0.61 – 5.74. The term subjective confidence interval is used since the interval is estimated from Monte Carlo Simulations and not observational data, i.e. it is not a real statistical confidence interval.

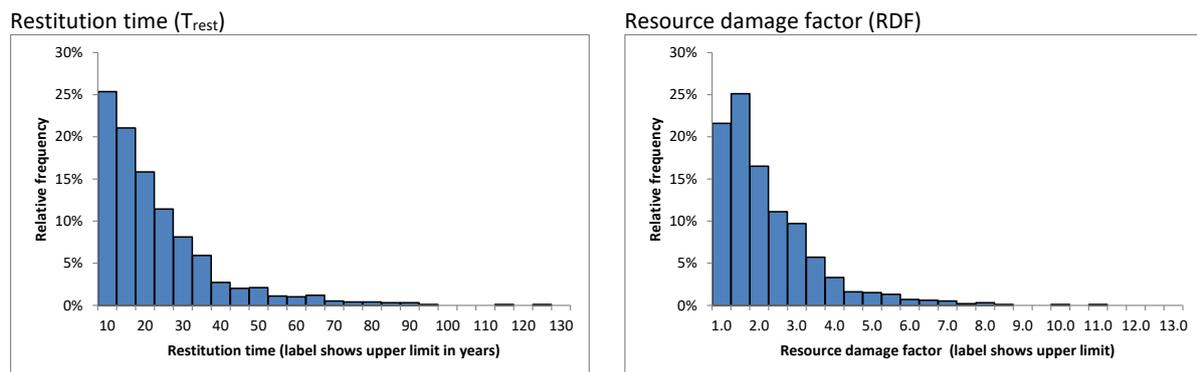


Figure 45. Histogram of the endpoint result given the uncertainty range and probability distribution of the input parameters presented in Table 12.

The results from the sensitivity analyses are presented in Figure 46.

All the model parameters have a statistically significant effect. The net fundamental reproductive rate (R) is ranked as the most important variable for both endpoints. More than half of the total variance observed in t_{res} (52%) and RDF (68%) in Figure 45 can be attributed to this parameter. The restitution time has similar sensitivity towards TLR and b (28% and 20%). The RDF is considerably less sensitive towards TLR, and only 5% of the variation observed in RDF in Figure 45 can be attributed to this parameter.

Parameter	T _{res}			RDF		
	Spearman Corr. Coeff.	p-values	Importance rank	Spearman Corr. Coeff.	p-values	Importance rank
R	-0.68	0.00	R	-0.80	0.00	R
b	-0.44	0.00	TLR	-0.51	0.00	b
TLR	0.51	0.00	b	0.19	0.00	TLR

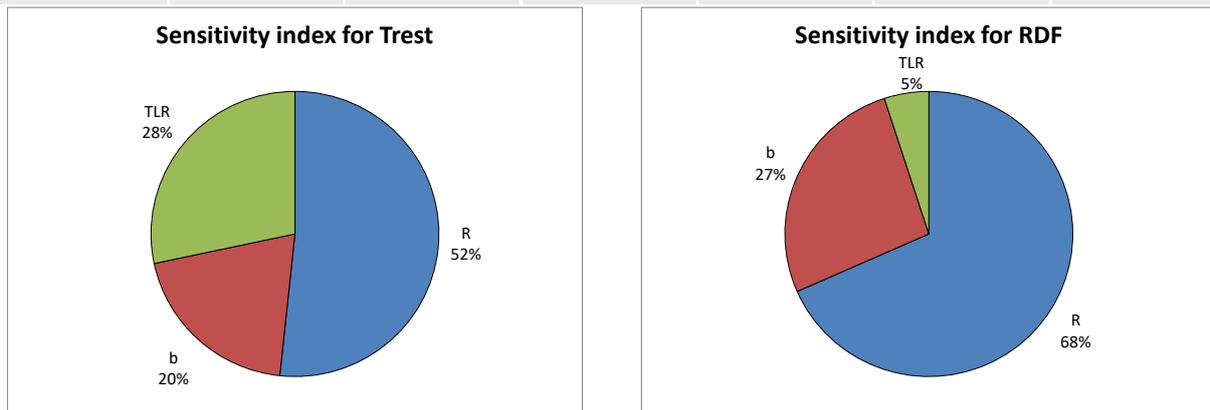
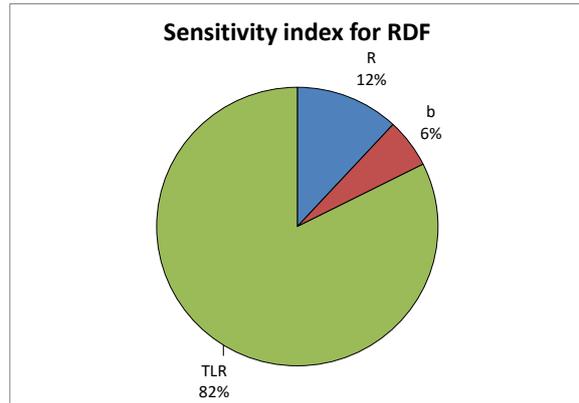
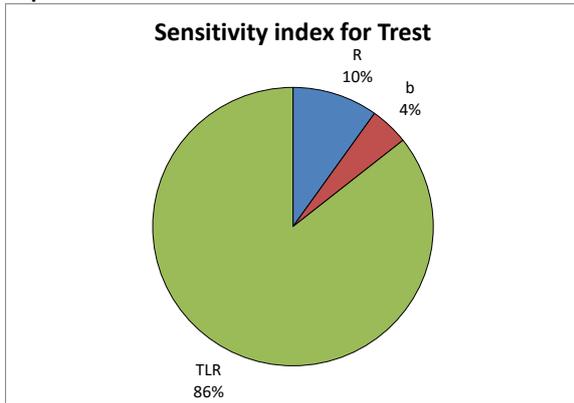


Figure 46. Result for the sensitivity analysis of T_{res} and RD for the following random variables: R =1.03-1.20, b = 0.5 – 1.0 b = 1 and TLR = 0.90-0.99. The population loss is held constant at 20%. The range of variation in the model parameters are R: 1.03 to 1.20, b: 0.5 to 1.5 and TLR: 0.90 to 0.99. A uniform probability distribution is assumed, i.e. all values within the range have equal probability (cf. Table 12).

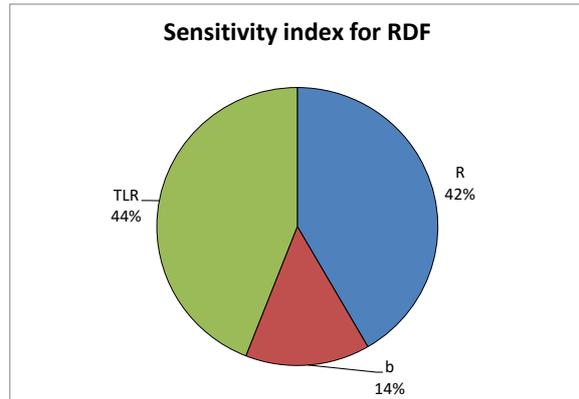
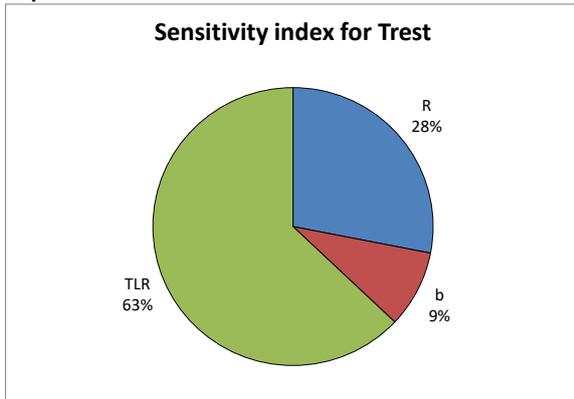
The population loss is held constant at 20% in the analyses. Decreasing the population loss will increase the relative importance of TLR while increasing the population loss will increase the relative importance of R and b (and decrease the importance of TLR). This is illustrated in Figure 47.

A biological explanation for this pattern is that a population will increase very slowly when the population size is large relative to the carrying capacity (i.e. small population loss) due to negative feedback (or constraint) on the population size. This is referred to as density dependent growth and the negative feedback on population growth may be caused by competition for various limited factors, such as food, space and mates. This will affect both populations with high and low fundamental net reproductive rates (R) and the realised population growth will be more like each other than their potential growth rates would indicate. At small population sizes relative to the carrying capacity (i.e. large population loss above a certain threshold level) there is less competition for the limiting factors and the population growth is faster. The realised population growth during the first years will be closer to the fundamental net reproductive rate and thus the relative importance of R and TLR will be different. As seen above, the parameter b is a factor that increase and decrease the relative importance of this competition and thus will follow the same pattern as the net fundamental reproductive rate (although not so important within the range tested).

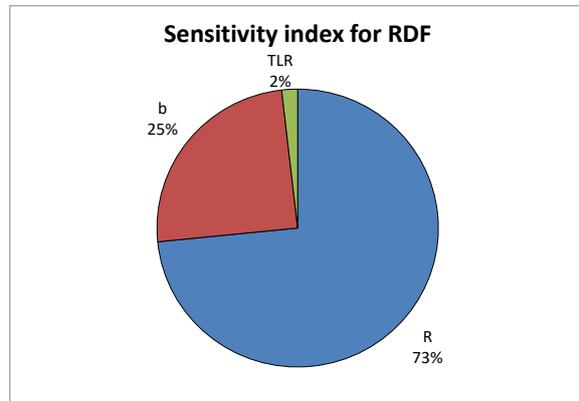
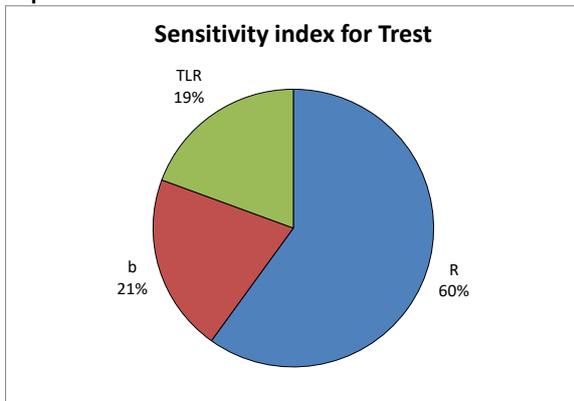
Population loss = 5%



Population loss = 10%



Population loss = 30%



Population loss = 50%

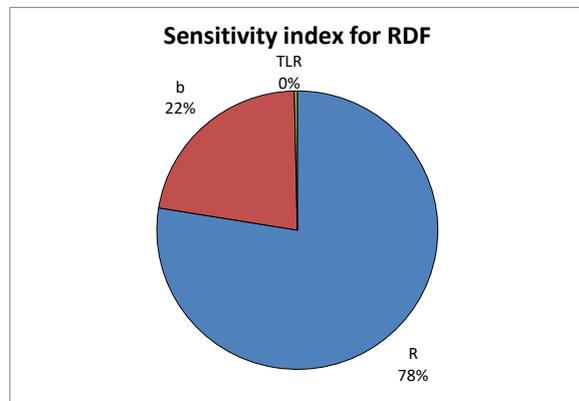
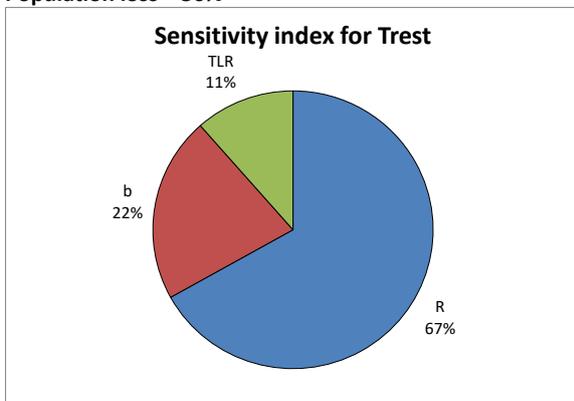


Figure 47. Illustration of how the relative importance of the model parameters varies for different population losses, measured by the sensitivity index.

4.1.3 Population vulnerability and comparison with the MIRA damage key

In this section, the restitution time for various population losses is calculated per wildlife group using the fundamental growth rates in Table 11 and the recommended settings for the other population model parameters, i.e. TLR = 0.95 and $b = 1$. This study is part of the comparison of the MIRA damage key and the ERA Acute population model. The result is therefore calculated and presented separately for the following population loss intervals:

- Interval 1: 5- 10%
- Interval 2: 10 – 20%
- Interval 3: 20-30%
- Interval 4: 30-99%

The MIRA population loss interval 1-5% is not included. In ERA Acute, a TLR of 0.95 yields a restitution time of 1 year + eventual lag-time and between 1 month and 3 years in MIRA. For each population loss interval 1,000 population losses are drawn, and 1,000 restitution times are estimated.

Results are presented in Figure 48 - Figure 75 with the following statistics and illustrations:

- (1) scatterplots showing the restitution times estimated from the population model for the given population loss interval, including a linear regression analysis were appropriate,
- (2) statistics for the central tendency and variation of the estimated restitution times for the population loss interval. The statistic referred to as “slope rate” is a measurement of the sensitivity of the population model for 1% population loss in the relevant interval. It is given as the number of years 1 percent population loss will increase/decrease the restitution time in the given population loss interval estimated from the linear regression. MIRA gives the restitution time based on pre-defined probability distribution of damage and the mean restitution time for the MIRA damage keys is estimated based on four assumptions explained in Appendix B.
- (3) histogram showing the proportion of the estimated restitution times with the population model that falls into damage categories with 1-year intervals (bins).
- (4) histogram showing the proportion of the estimated restitution times with the population model that falls into MIRA damage keys categories. The bin size or restitution time intervals in MIRA are: Damage category 1: 1 month to 1 year, Damage category 2: 1 – 3 years, Damage category 3: 3-10 years and Damage category 4: more than 10 years.

The restitution range (y-axis) of the scatterplots is set to 20 years for easier comparison of the plots (“slope rates”) for different population loss intervals and between different wildlife groups. For wildlife group 7 (toothed whales, sea cows, sea turtles) the range of the y-axis is 30 years.

As is evident in the result figures, the estimated restitution times appears as small “steps” within the intervals that may be approximated with a linear curve for population losses in the intervals 1-3. The slope and width of the curve is a measurement of the sensitivity of both the population model and the wildlife group for population loss in the relevant interval. A steeper curve (slope) in a population interval means that the population model (and thus the population for the wildlife group) is more sensitive to population loss in the given interval.

The “slope rate” is the number of years an added 1% population loss will increase the restitution time for the given population loss interval, estimated from the linear regression. In the last population loss interval, 30-99% the restitution time curve is not linear. At large population losses (from 60% and above depending on wildlife group) the slope is large, meaning that an increase in population loss in this interval is much more important than in the previous intervals. For example, a 10% extra loss in the end of the curve for wildlife group 6 results in an addition restitution time of ca. 45 years, while the same 10% loss in the beginning of the curve in this interval results in an addition restitution time of 7 years.

This is similar to the *critical population density* used in the fish model, and although not reflected in the per capita growth rate, the population growth will be very slow. In nature, such effect is often attributed to mate limitation, corporative defence and/or feeding as well as loss of genetic diversity and vulnerable for demographic stochasticity. Some other attributes of the model are:

- Each wildlife group (WG) (or VEC-group) has different growth factor representing typical life history traits for species in the group
- The seven WGs have large differences in life history traits and thus the population vulnerabilities (population growth rate) differ greatly between the VEC-groups
- Growth rate also depends on population loss according to theory of density-dependent processes (population growth rates varies depending on population size within a VEC-group)
- Better resolution and no aggregation of results within the calculation steps
- The user may use population specific or generic and standard values for all parameters in the model
- Will not give results below Threshold Level for Recovery

Conclusion comparison with MIRA damage keys:

1. ERA Acute distinguishes between population vulnerability for different VECs
2. ERA Acute yields on average longer restitution times for all WGs, except WG4 (cormorants, shags, divers, ducks and geese) where it yields equal or possible slightly shorter restitution times than MIRA
3. ERA Acute yields significant longer restitution times for WG1 (albatrosses and skuas), WG7 (toothed whales, sea cows and sea turtles) and partly WG6 (walrus, polar bears, sea otter and European otter)

The mean restitution time estimated by the population model for different wildlife groups and population loss intervals is presented in Table 13.

Table 13. Mean restitution time estimated by the population model for different wildlife groups and population loss intervals. The restitution time is estimated using default values for the fundamental growth rate. For the wildlife group referred to WG All in the last column, the growth factor used is drawn from a uniform distribution ranging from 1.03 to 1.20. See Figure 48 to Figure 75 for details.

Population loss intervals	WG1	WG2	WG3	WG4	WG5	WG6	WG7	WG All
1-5%	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
5-10%	9.1	4.8	3.4	2.8	3.8	7.5	14.4	5.2
10-20%	24.9	12.9	9.0	7.1	10.2	21.4	40.8	14.4
20-30%	38.2	19.8	13.7	10.6	15.6	32.0	62.7	21.7
30-100%	76.8	40.3	27.6	20.8	31.4	64.9	122.0	44.4

WG1 (albatrosses and skuas): Population loss 5-10%

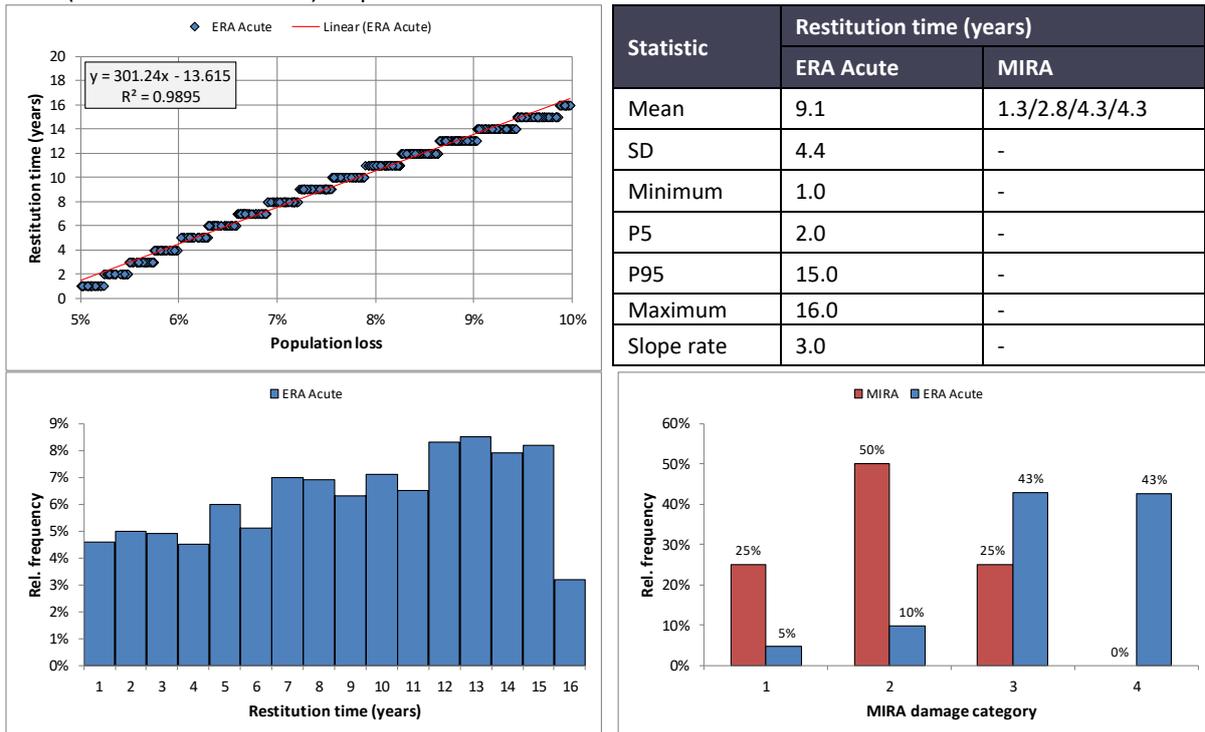


Figure 48. Estimated restitution time for population loss between 5 and 10%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG1 (albatrosses and skuas): Population loss 10-20%

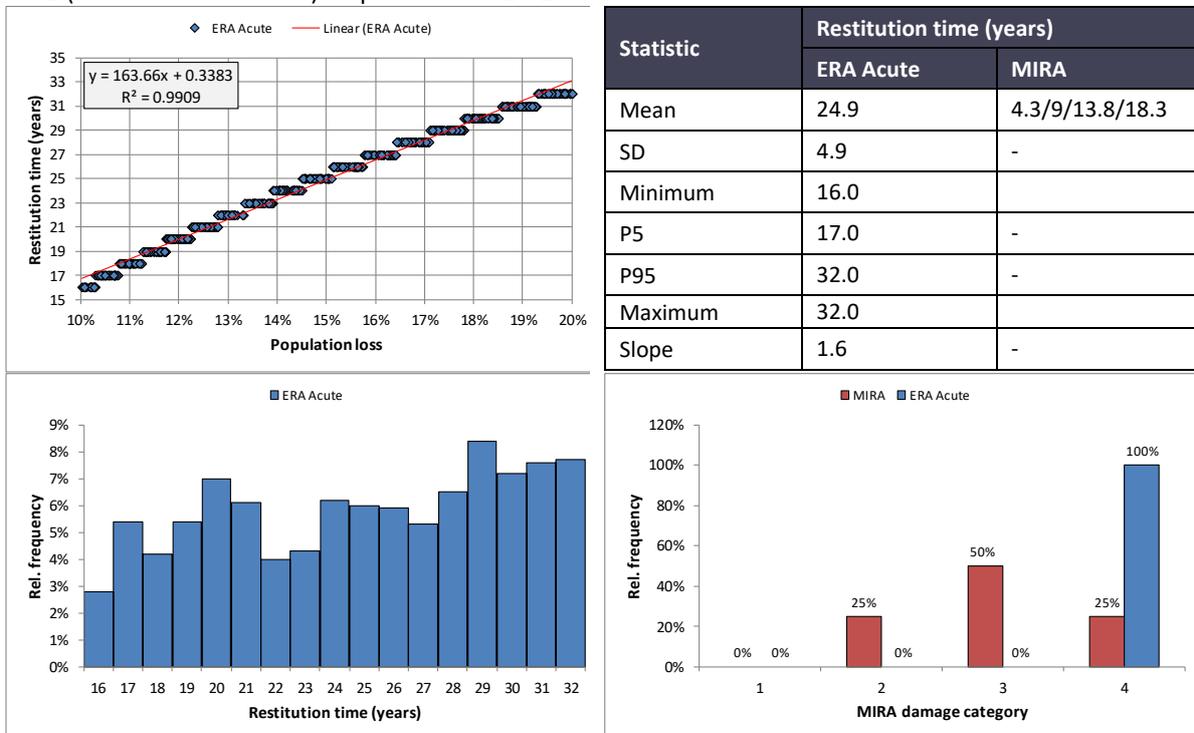


Figure 49. Estimated restitution time for population loss between 10 and 20%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG1 (albatrosses and skuas): Population loss 20-30%

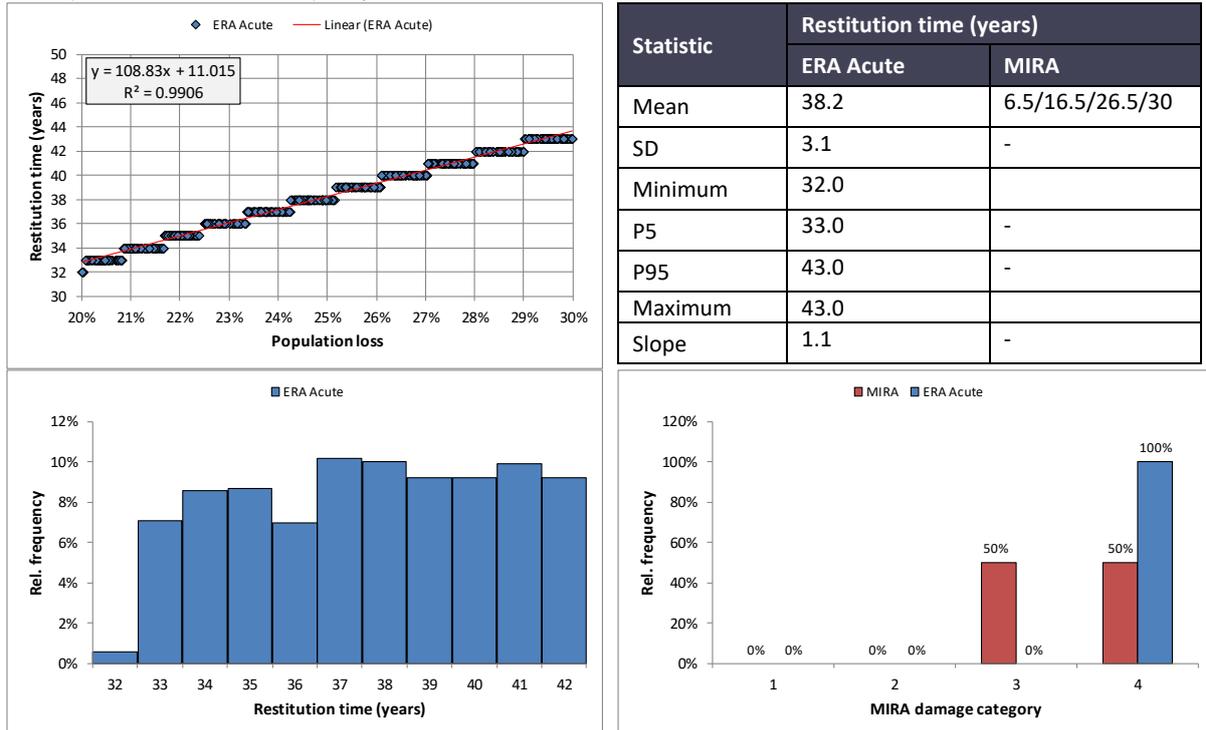


Figure 50. Estimated restitution time for population loss between 20 and 30%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG1 (albatrosses and skuas): Population loss 30-99%

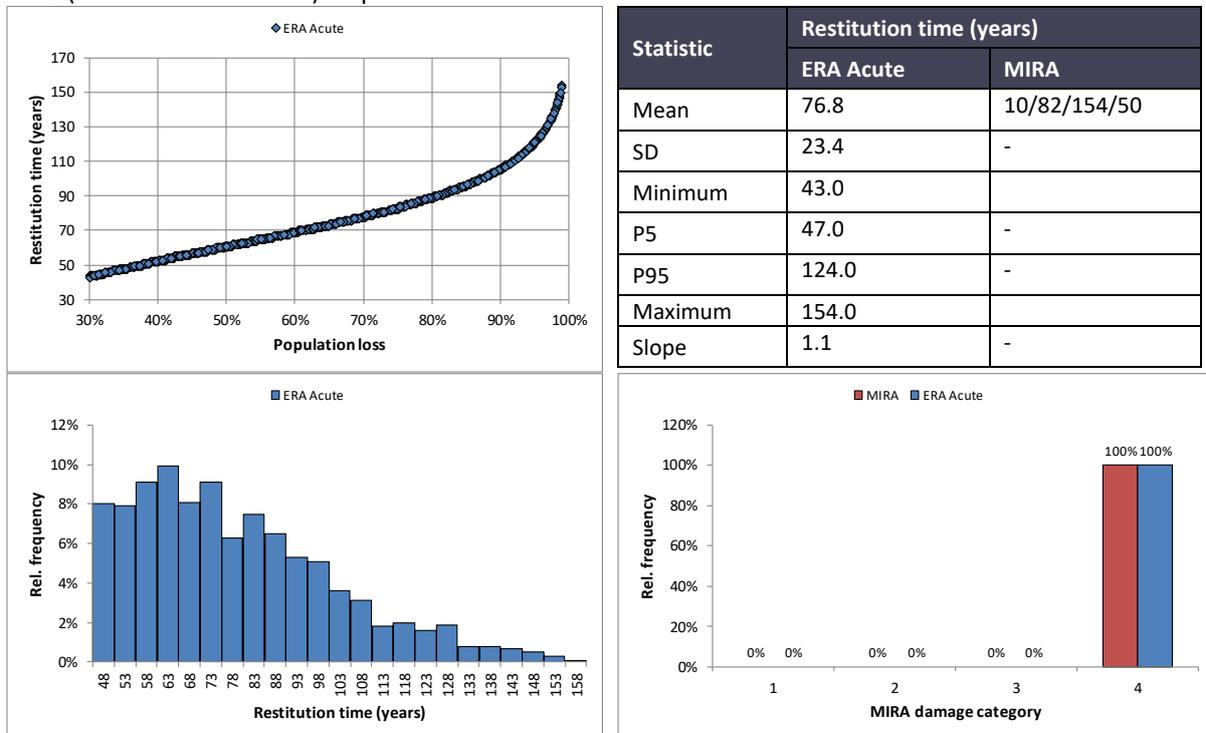


Figure 51. Estimated restitution time for population loss between 30 and 99%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 5-years categories (bottom right) and MIRA damage categories (bottom right).

WG2 (auks, petrels and shearwater): Population loss 5-10%

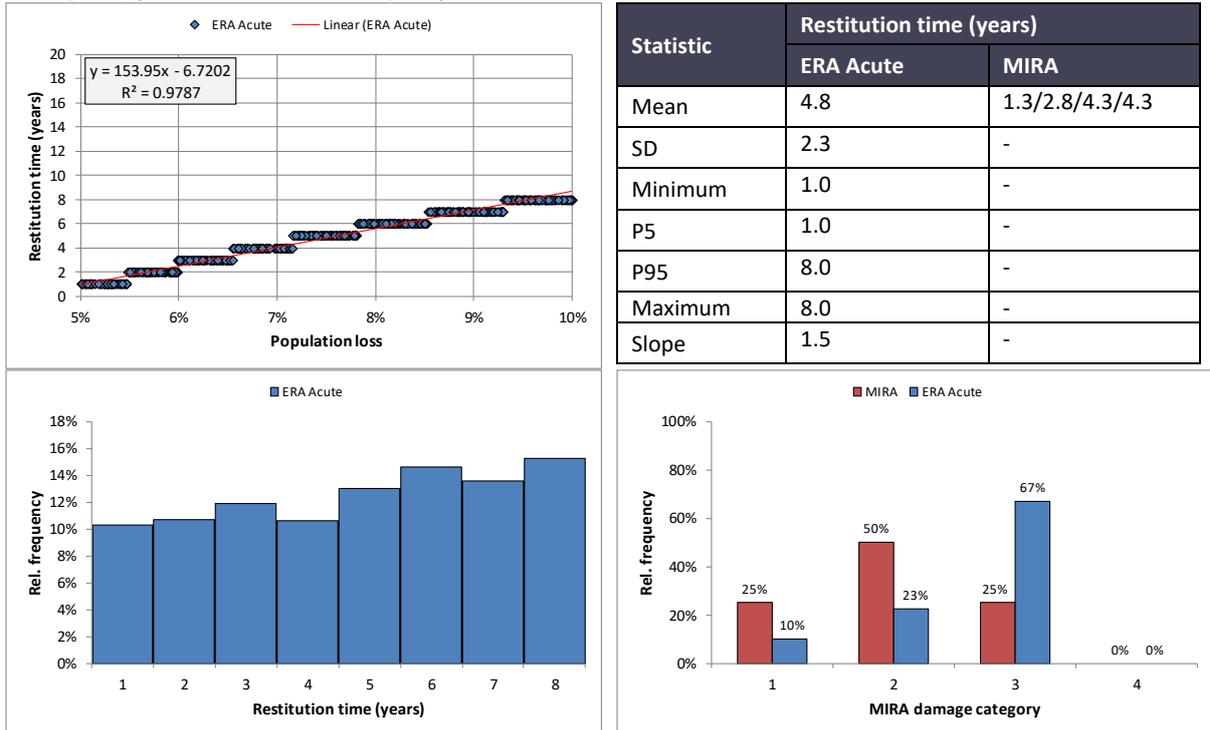


Figure 52. Estimated restitution time for population loss between 5 and 10%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG2 (auks, petrels and shearwater): Population loss 10-20%

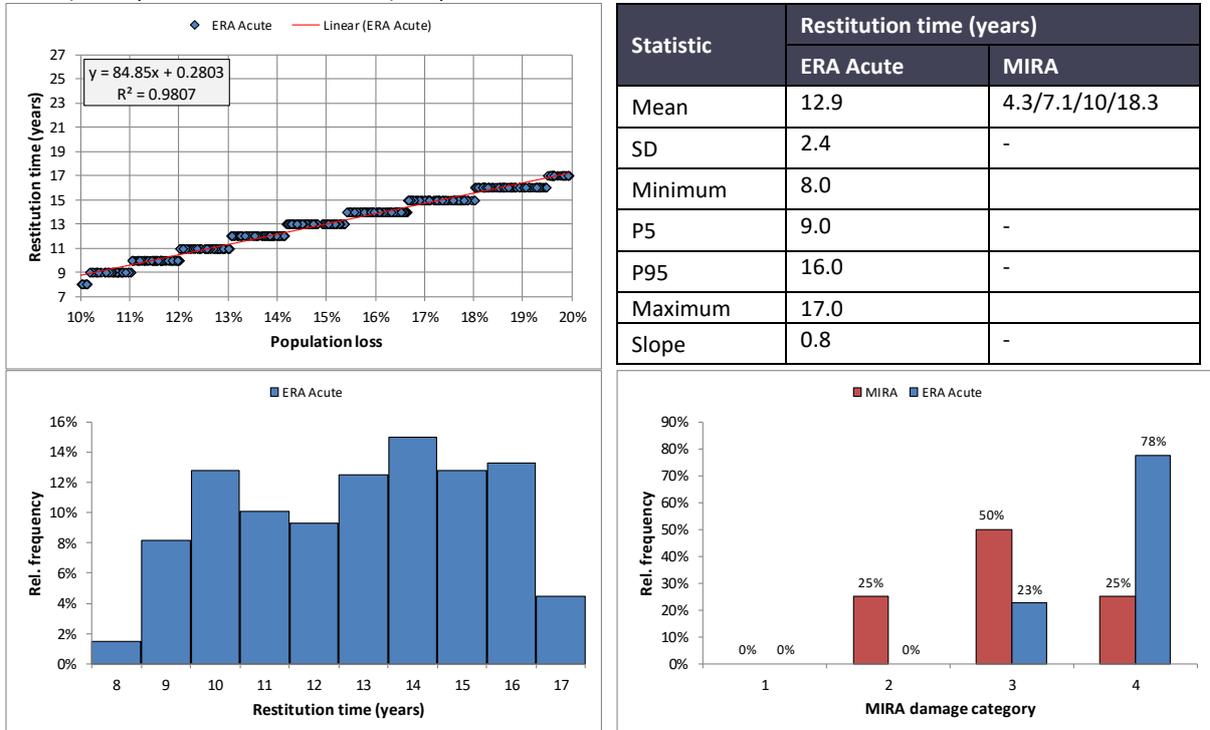


Figure 53. Estimated restitution time for population loss between 10 and 20%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG2 (auks, petrels and shearwater): Population loss 20-30%

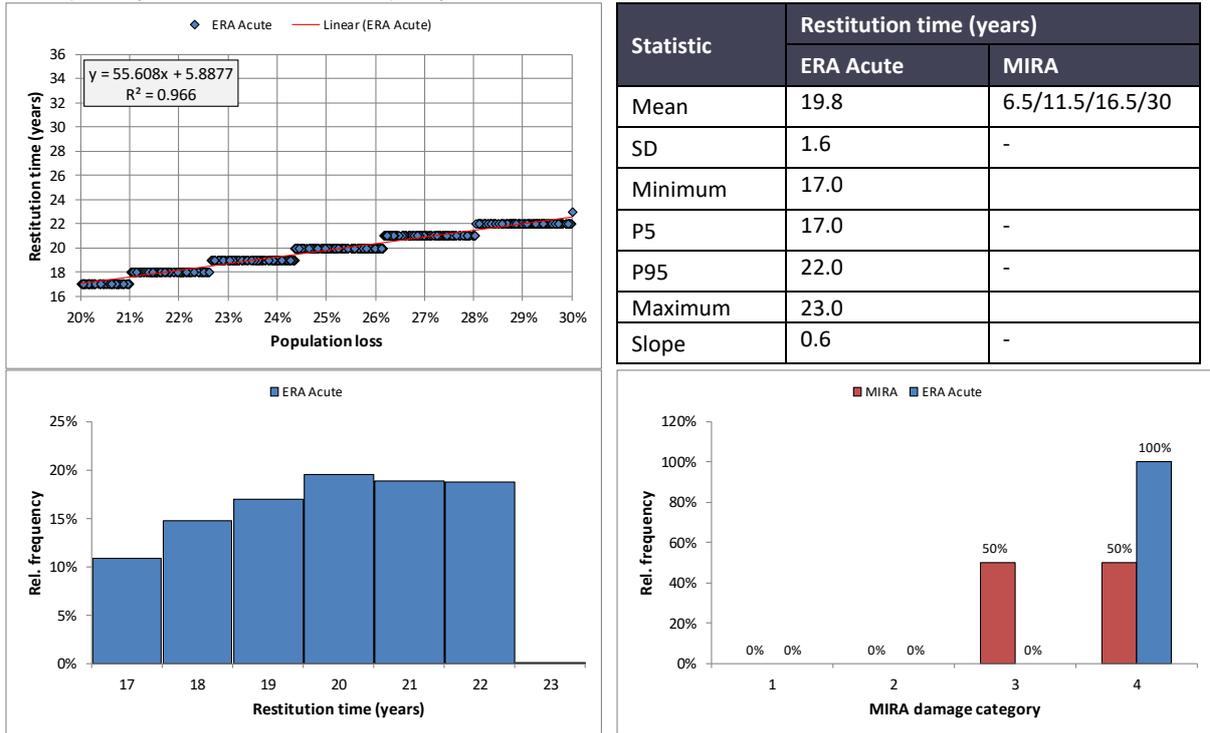


Figure 54. Estimated restitution time for population loss between 20 and 30%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG2 (auks, petrels and shearwater): Population loss 30-99%

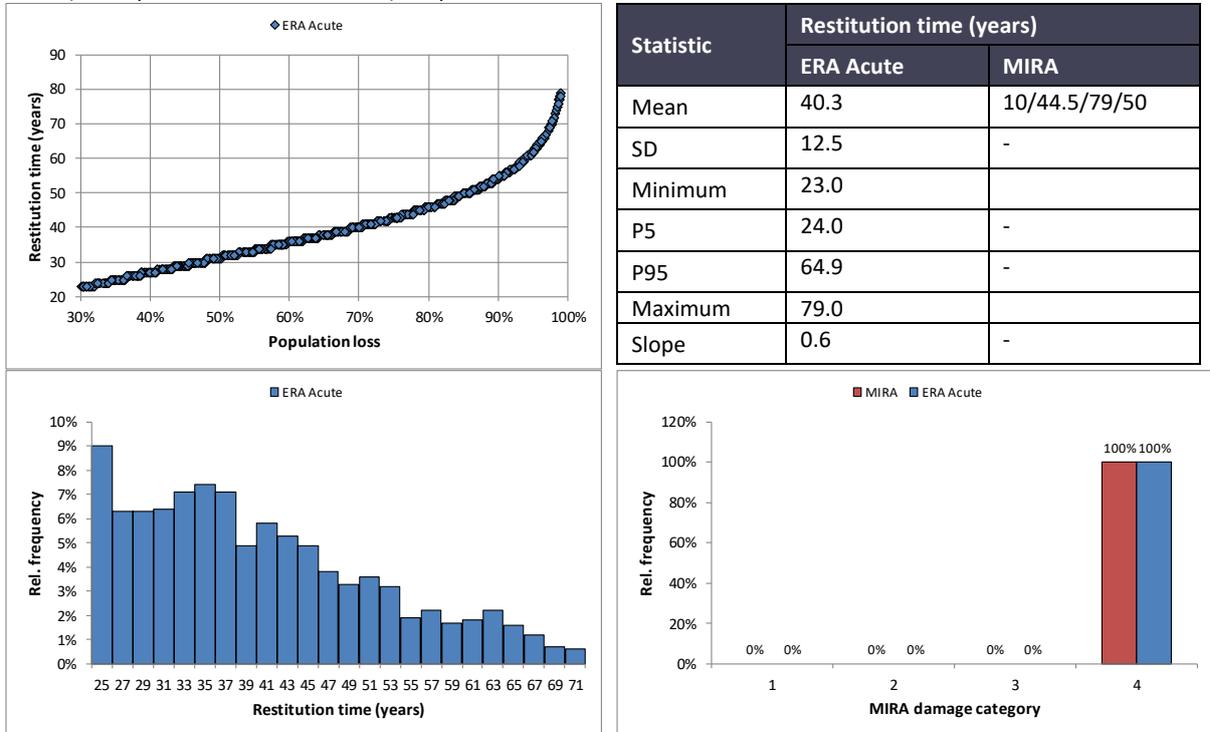


Figure 55. Estimated restitution time for population loss between 30 and 99%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 2-years categories (bottom right) and MIRA damage categories (bottom right).

WG3 (gannets, penguins, gulls and terns): Population loss 5-10%

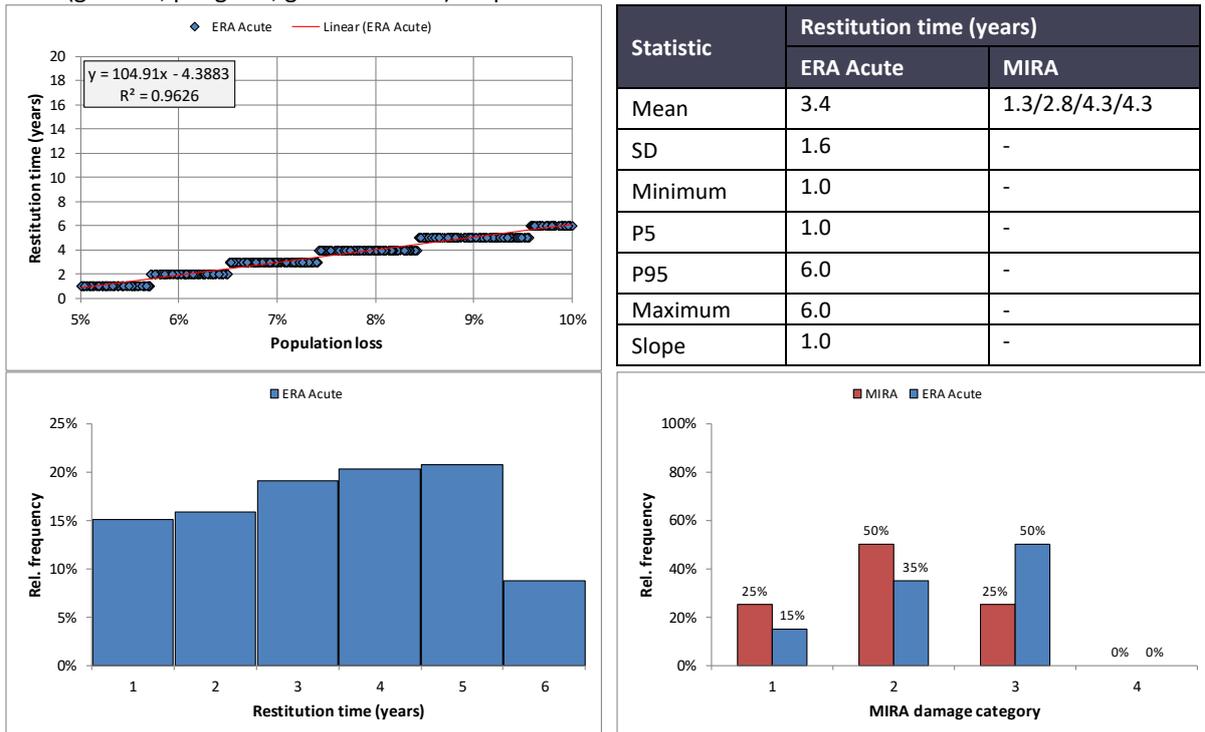


Figure 56. Estimated restitution time for population loss between 5 and 10%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG3 (gannets, penguins, gulls and terns): Population loss 10-20%

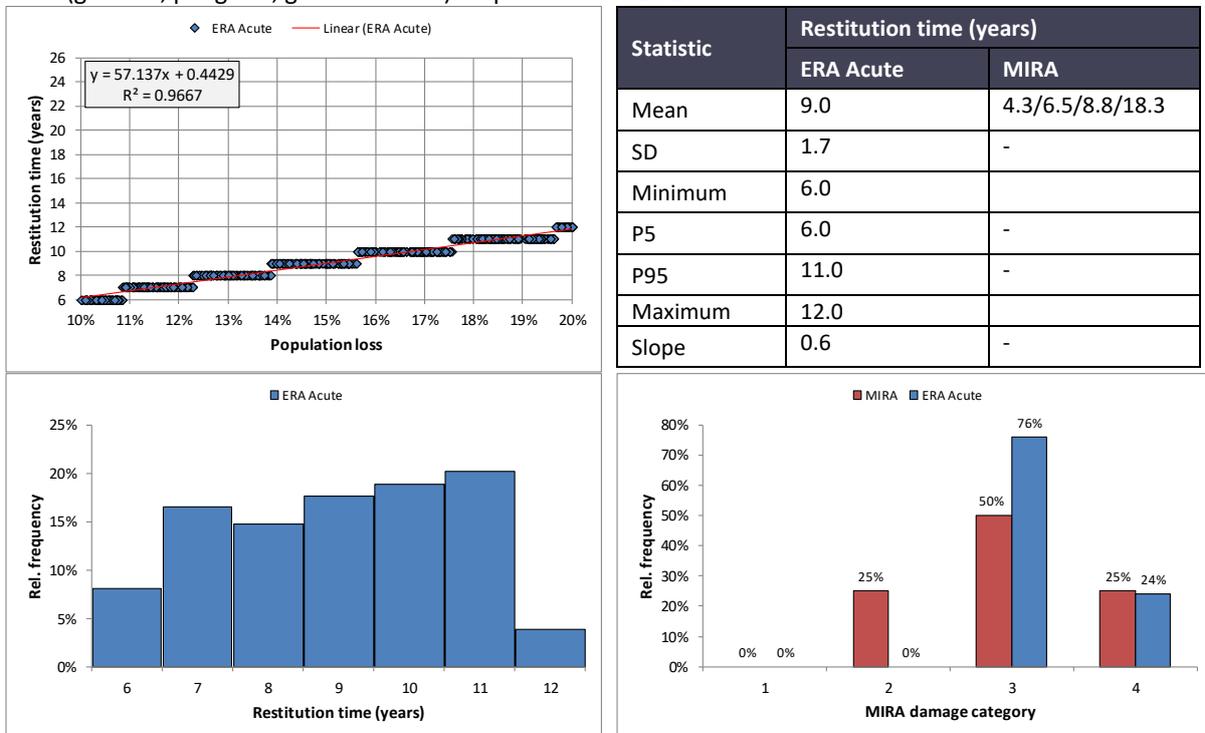


Figure 57. Estimated restitution time for population loss between 10 and 20%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG3 (gannets, penguins, gulls and terns): Population loss 20-30%

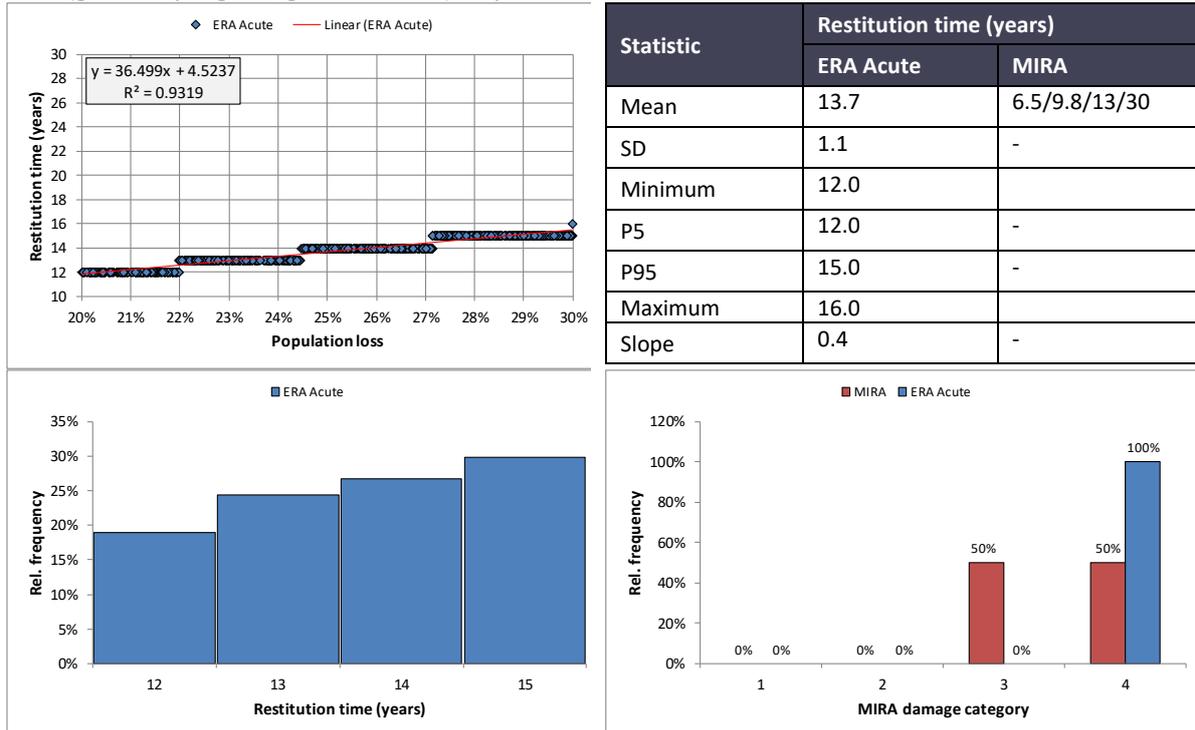


Figure 58. Estimated restitution time for population loss between 20 and 30%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG3 (gannets, penguins, gulls and terns): Population loss 30-99%

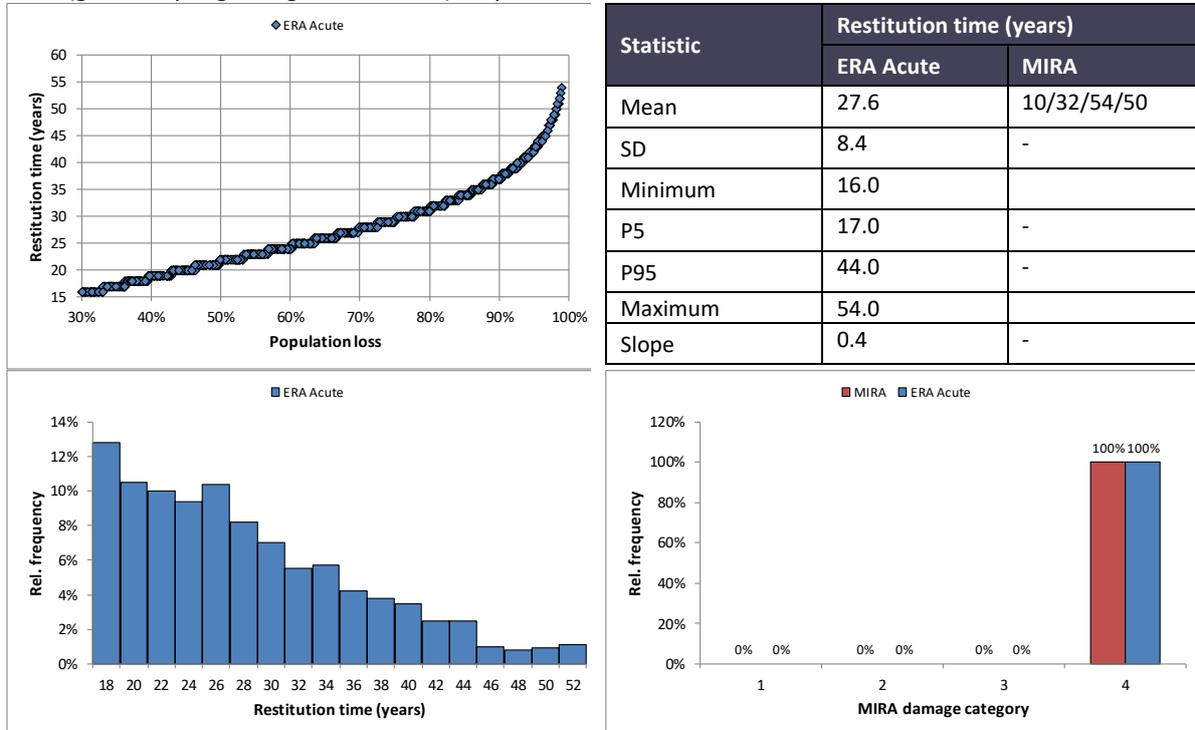


Figure 59. Estimated restitution time for population loss between 30 and 99%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 2-years categories (bottom right) and MIRA damage categories (bottom right).

WG4 (cormorants, shags, divers, ducks and geese): Population loss 5-10%

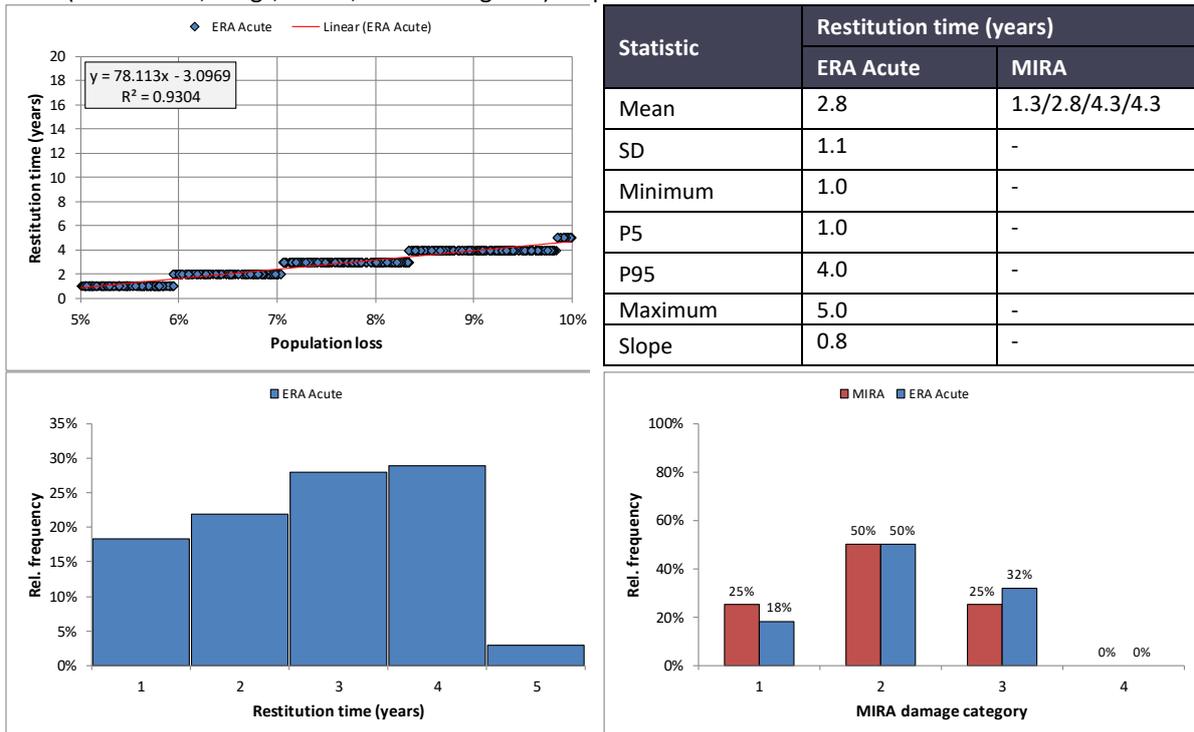


Figure 60. Estimated restitution time for population loss between 5 and 10%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG4 (cormorants, shags, divers duck and goose): Population loss 10-20%

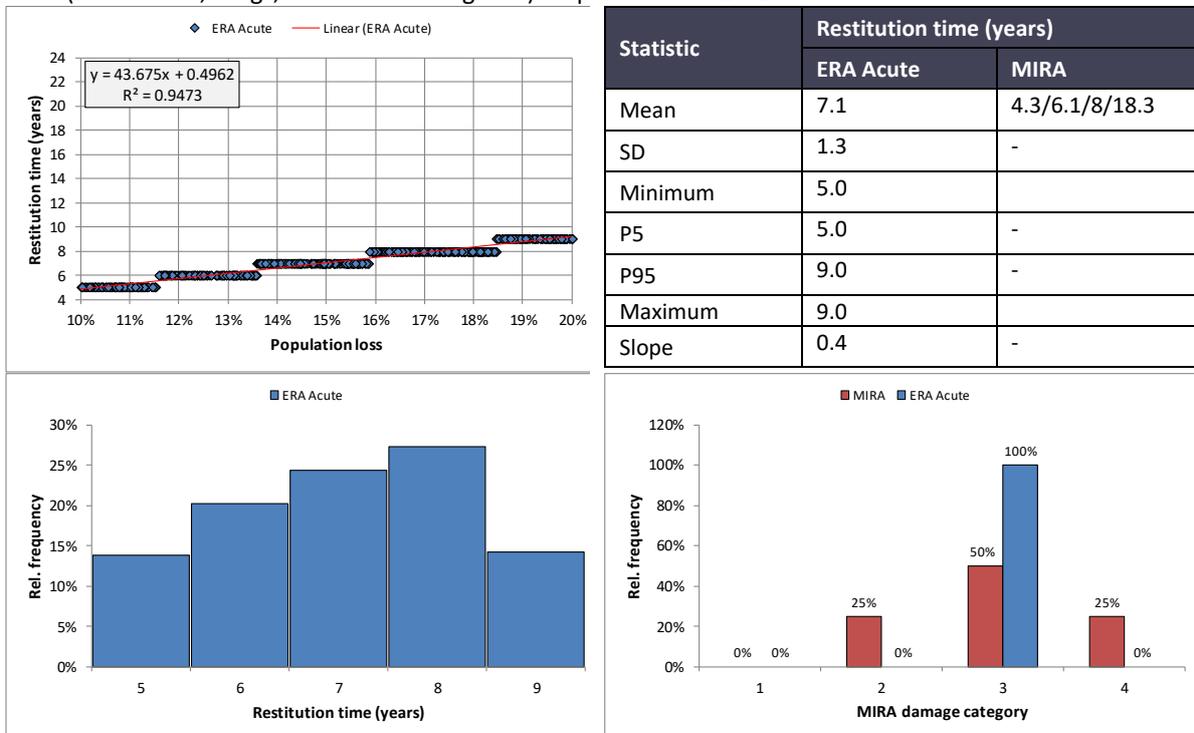


Figure 61. Estimated restitution time for population loss between 10 and 20%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG4 (cormorants, shags, divers, ducks and geese): Population loss 20-30%

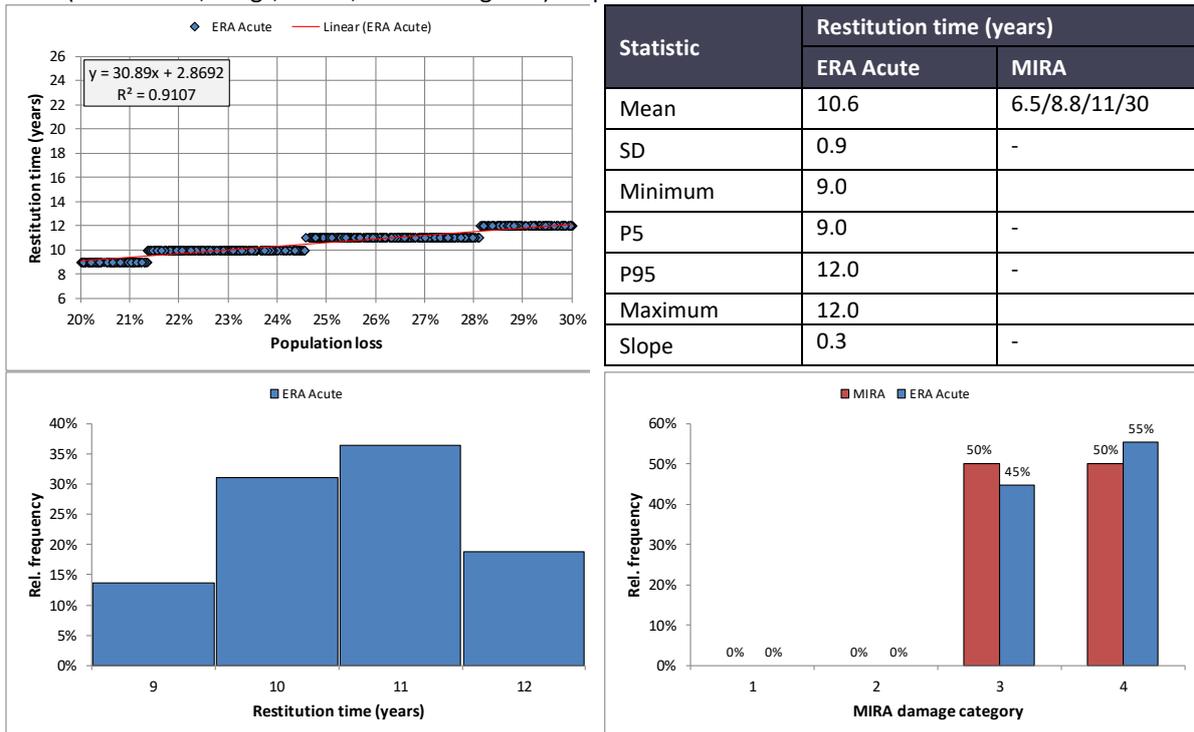


Figure 62. Estimated restitution time for population loss between 20 and 30%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG4 (cormorants, shags, divers ducks and geese): Population loss 30-99%

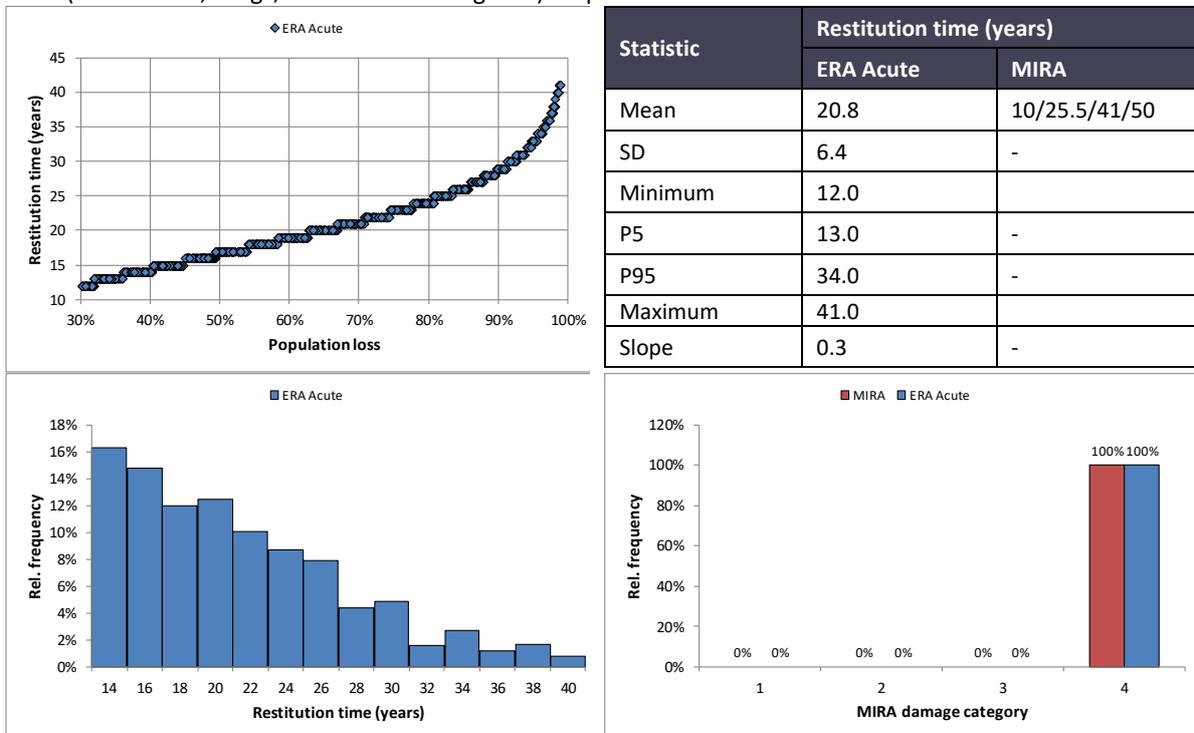


Figure 63. Estimated restitution time for population loss between 30 and 99%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 2-years categories (bottom right) and MIRA damage categories (bottom right).

WG5 (true seals, sea lions, fur seals, baleen whales): Population loss 5-10%

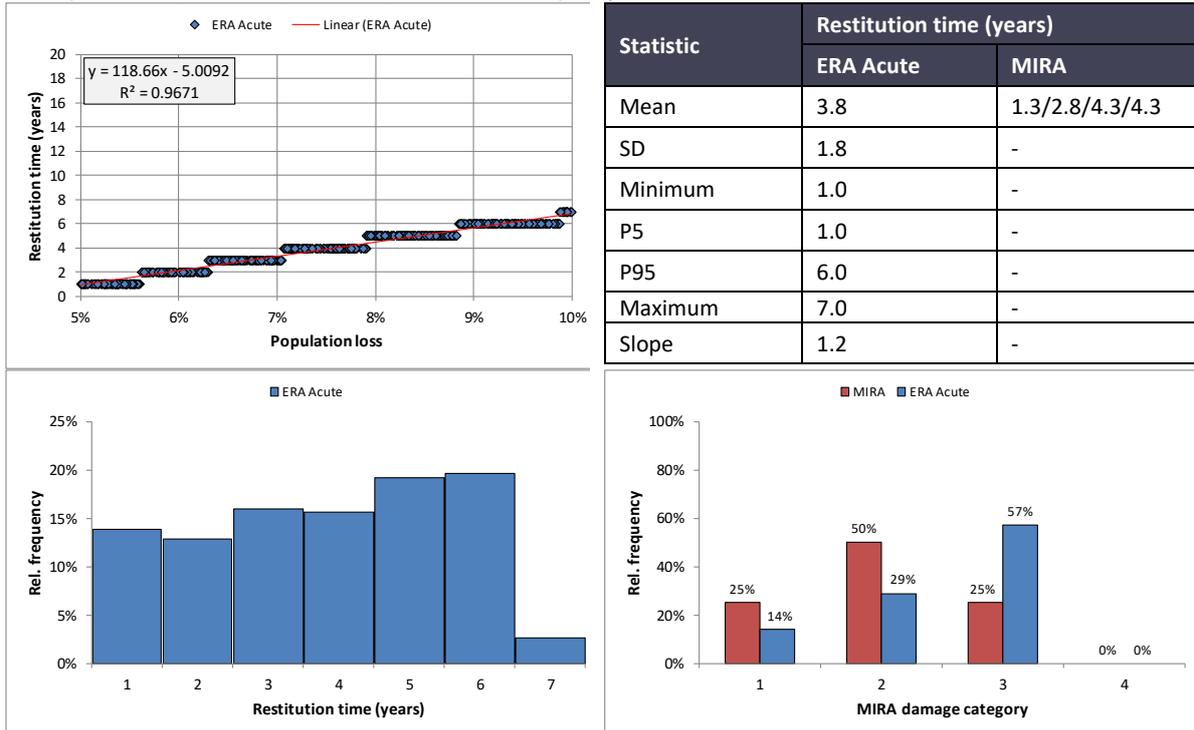


Figure 64. Estimated restitution time for population loss between 5 and 10%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-years categories (bottom right) and MIRA damage categories (bottom right).

WG5 (true seals, sea lions, fur seals, baleen whales): Population loss 10-20%

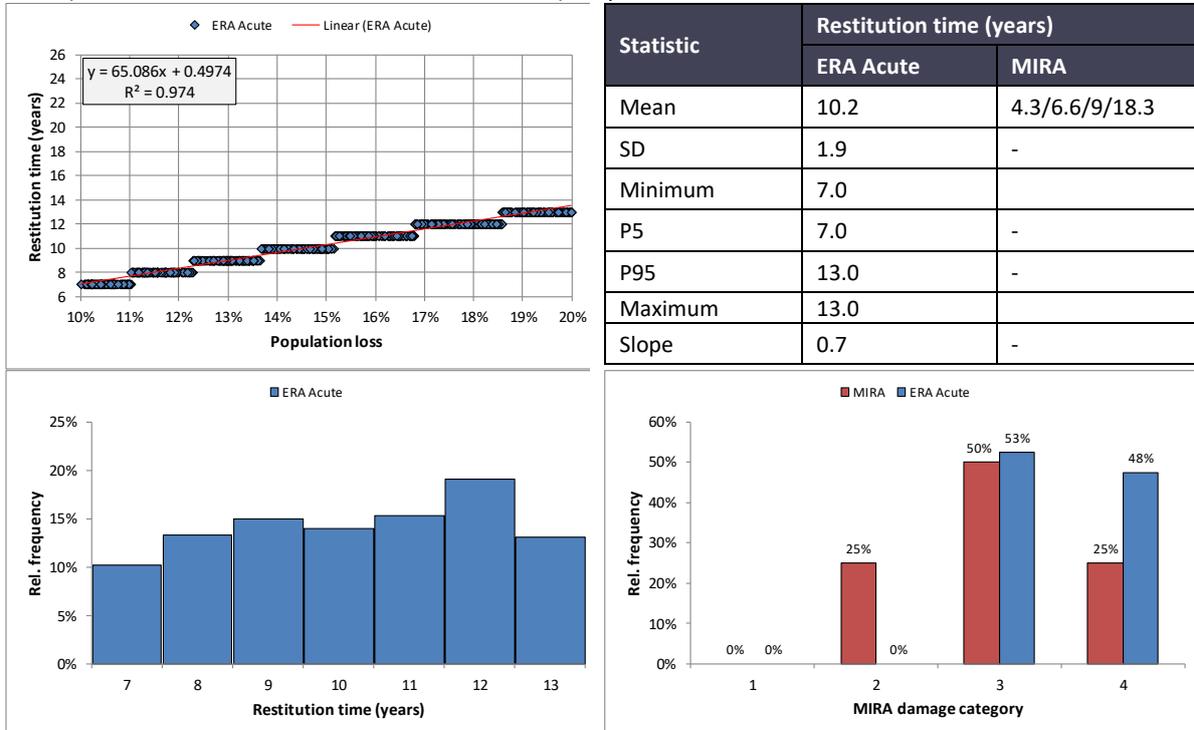


Figure 65. Estimated restitution time for population loss between 10 and 20%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG5 (true seals, sea lions, fur seals, baleen whales): Population loss 20-30%

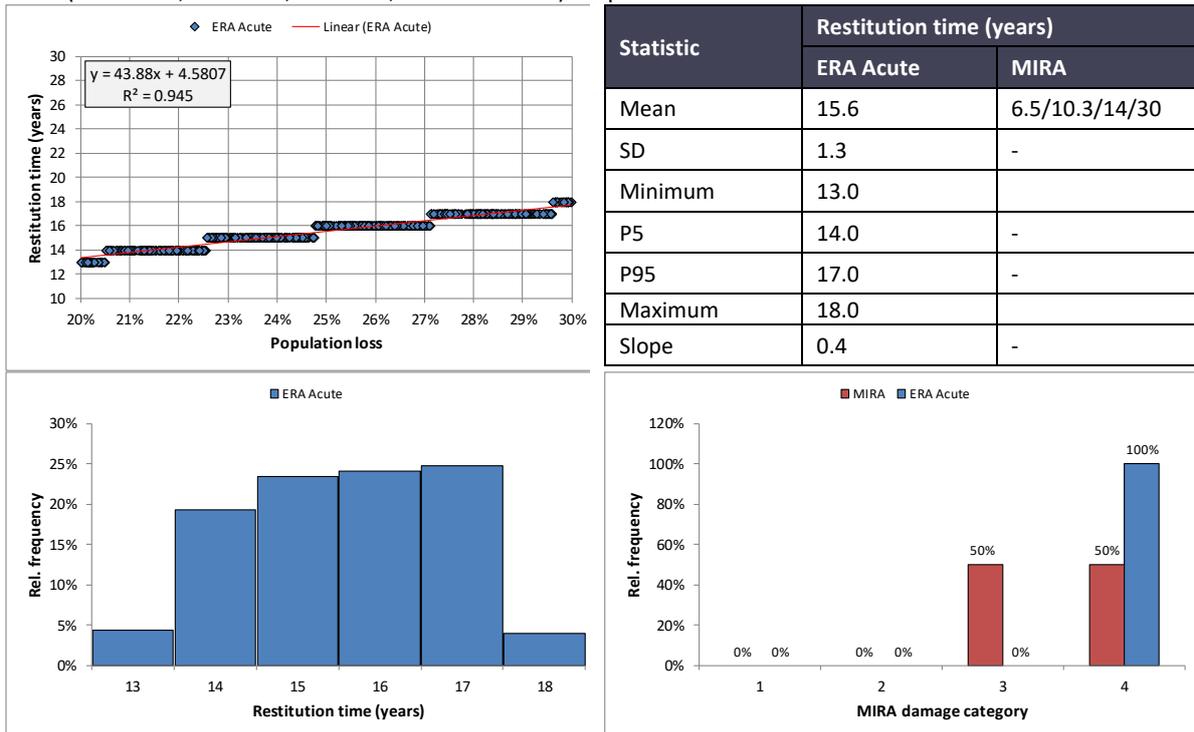


Figure 66. Estimated restitution time for population loss between 20 and 30%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG5 (true seals, sea lions, fur seals, baleen whales): Population loss 30-99%

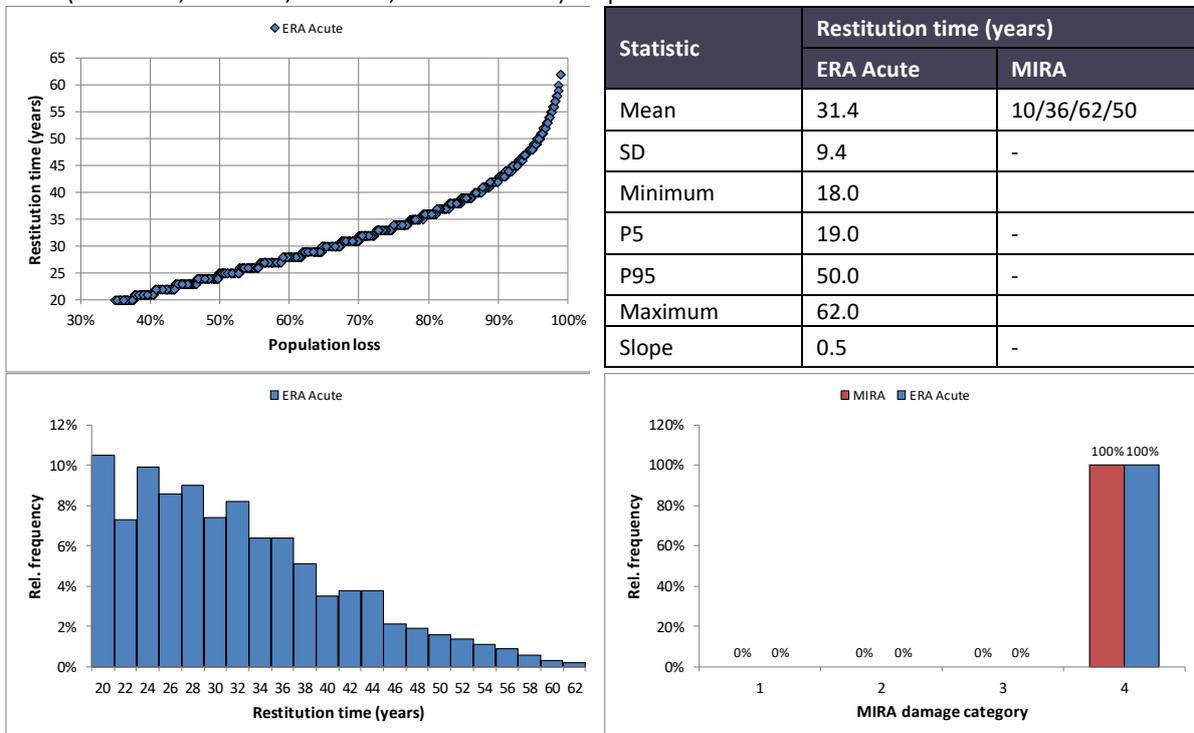


Figure 67. Estimated restitution time for population loss between 30 and 99%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 2-years categories (bottom right) and MIRA damage categories (bottom right).

WG6 (walrus, aquatic mammals): Population loss 5-10%

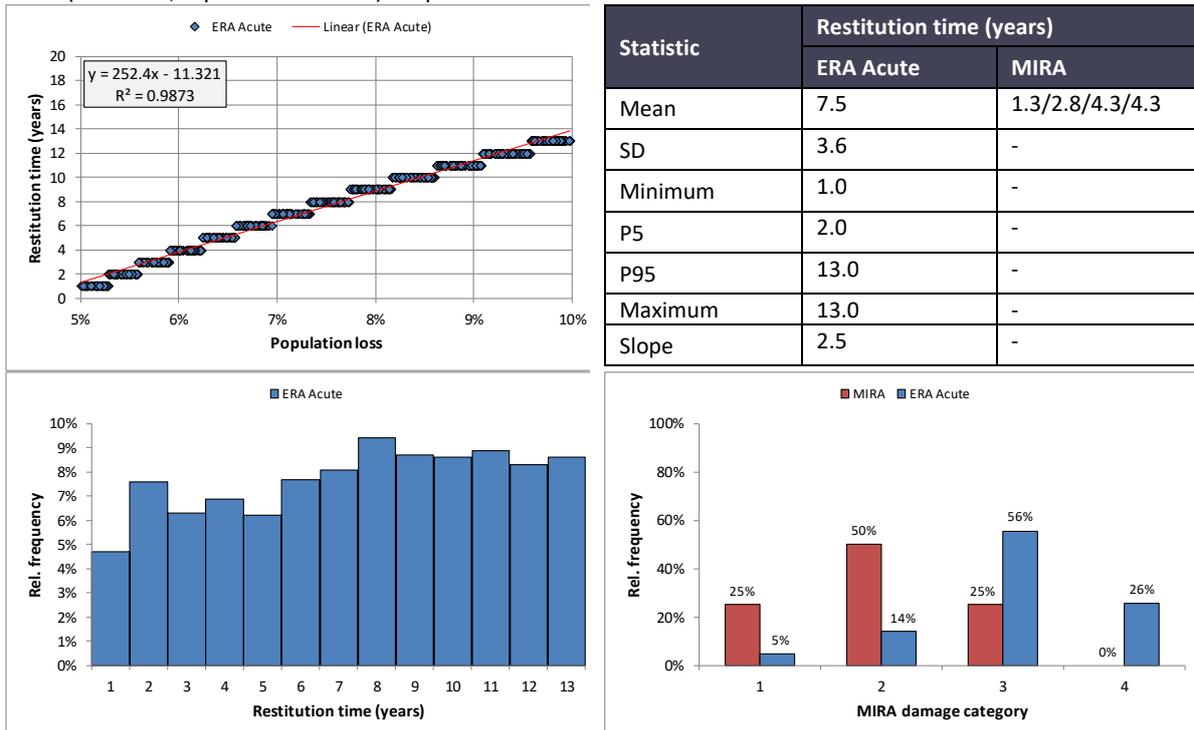


Figure 68. Estimated restitution time for population loss between 5 and 10%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-years categories (bottom right) and MIRA damage categories (bottom right).

WG6 (walrus, aquatic mammals): Population loss 10-20%

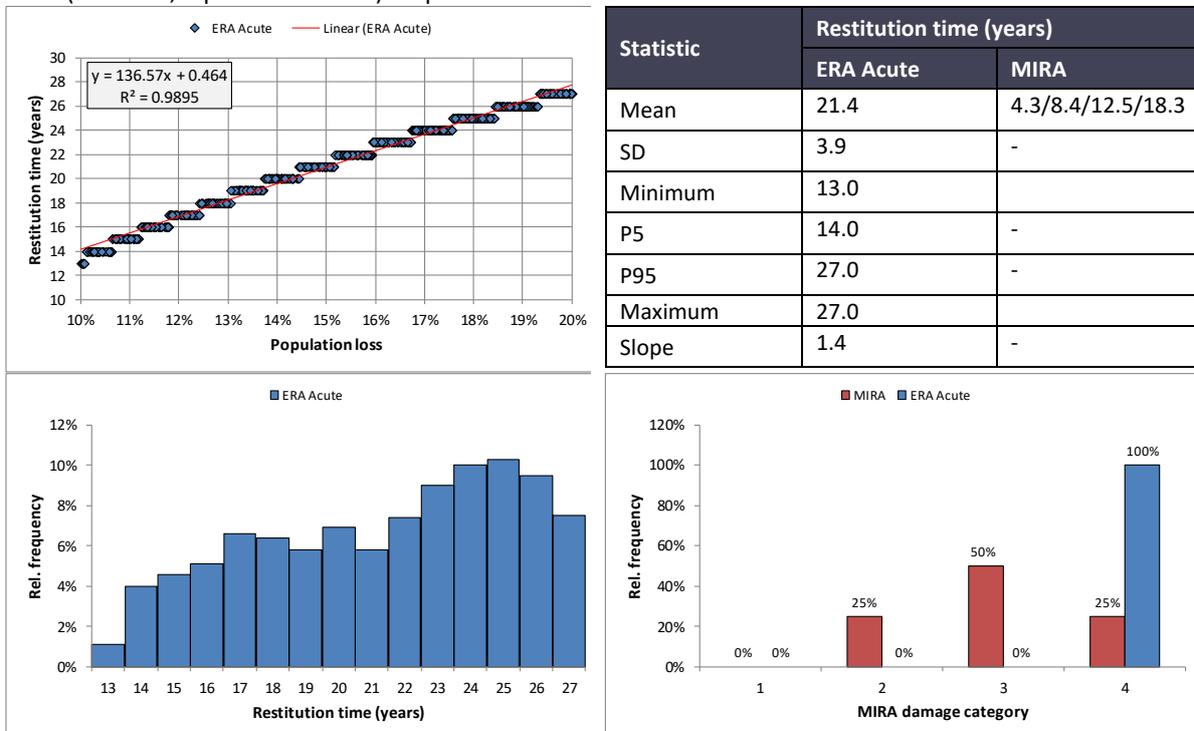


Figure 69. Estimated restitution time for population loss between 10 and 20%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG6 (walrus, aquatic mammals): Population loss 20-30%

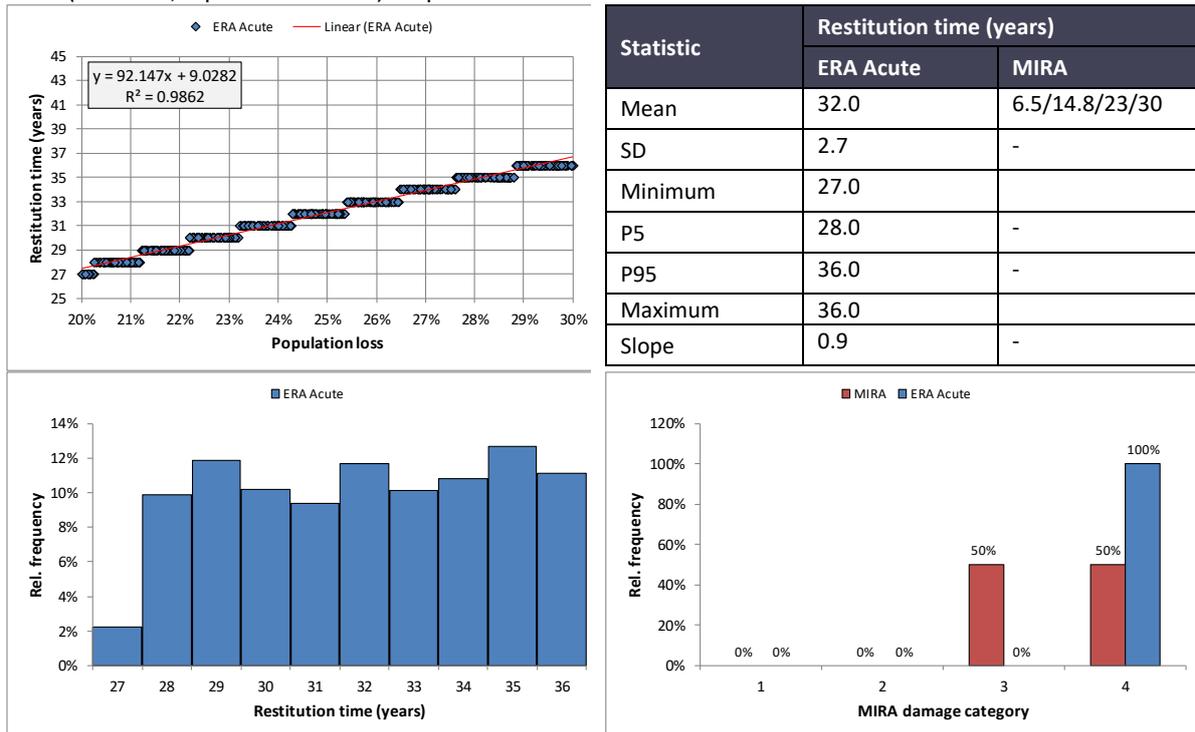


Figure 70. Estimated restitution time for population loss between 20 and 30%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG6 (walrus, aquatic mammals): Population loss 30-99%

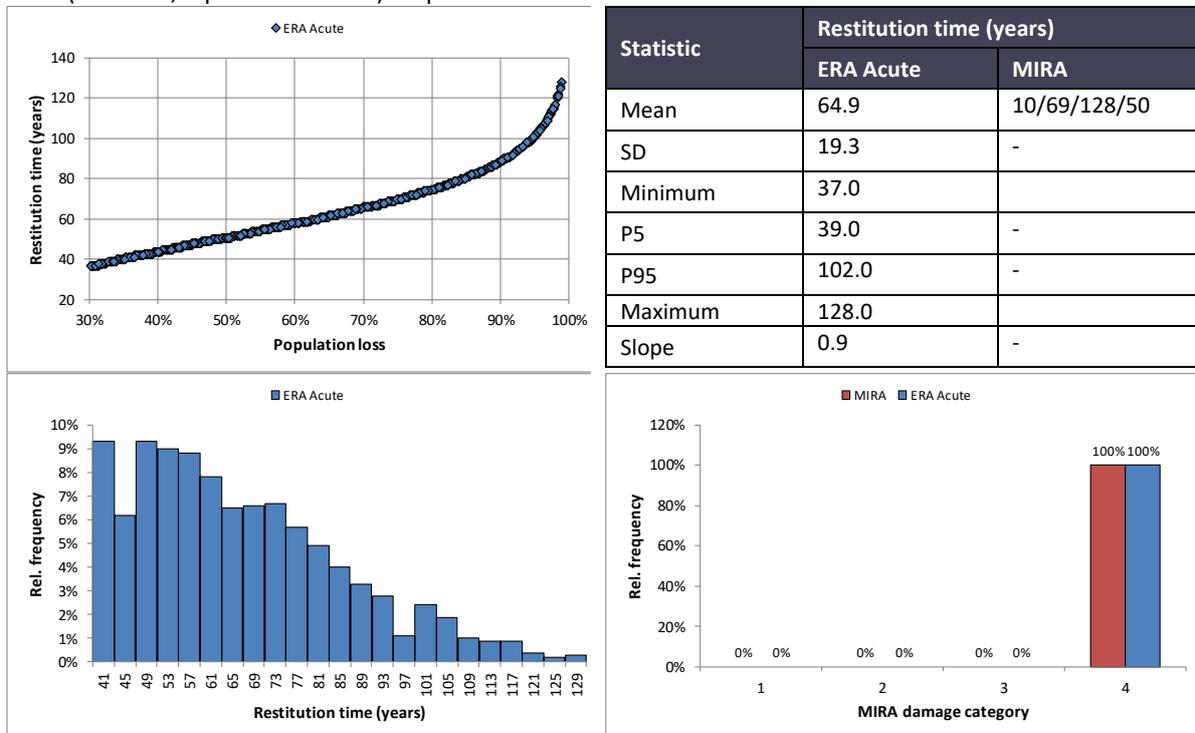


Figure 71. Estimated restitution time for population loss between 30 and 99%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 4-years categories (bottom right) and MIRA damage categories (bottom right).

WG7 (toothed whales, sea cows, sea turtles): Population loss 5-10%

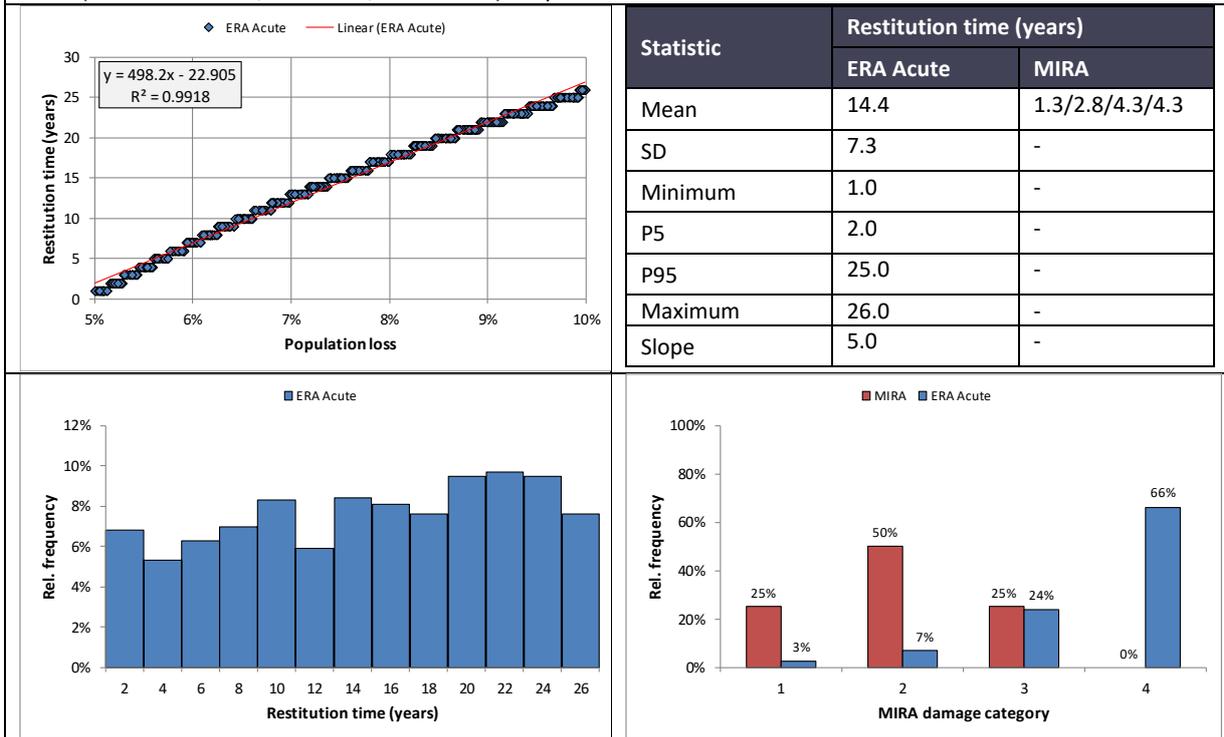


Figure 72. Estimated restitution time for population loss between 5 and 10%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 2-years categories (bottom right) and MIRA damage categories (bottom right).

WG7 (toothed whales, sea cows, sea turtles): Population loss 10-20%

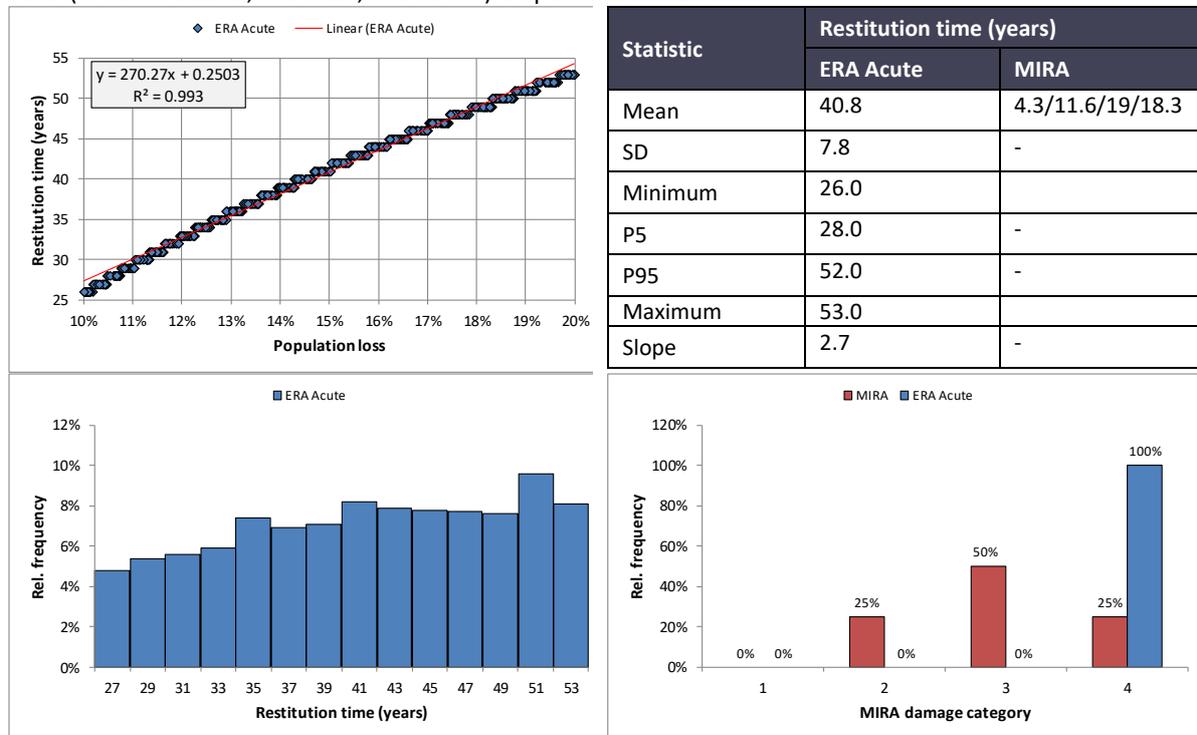


Figure 73. Estimated restitution time for population loss between 10 and 20%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 2-years categories (bottom right) and MIRA damage categories (bottom right).

WG7 (toothed whales, sea cows, sea turtles): Population loss 20-30%

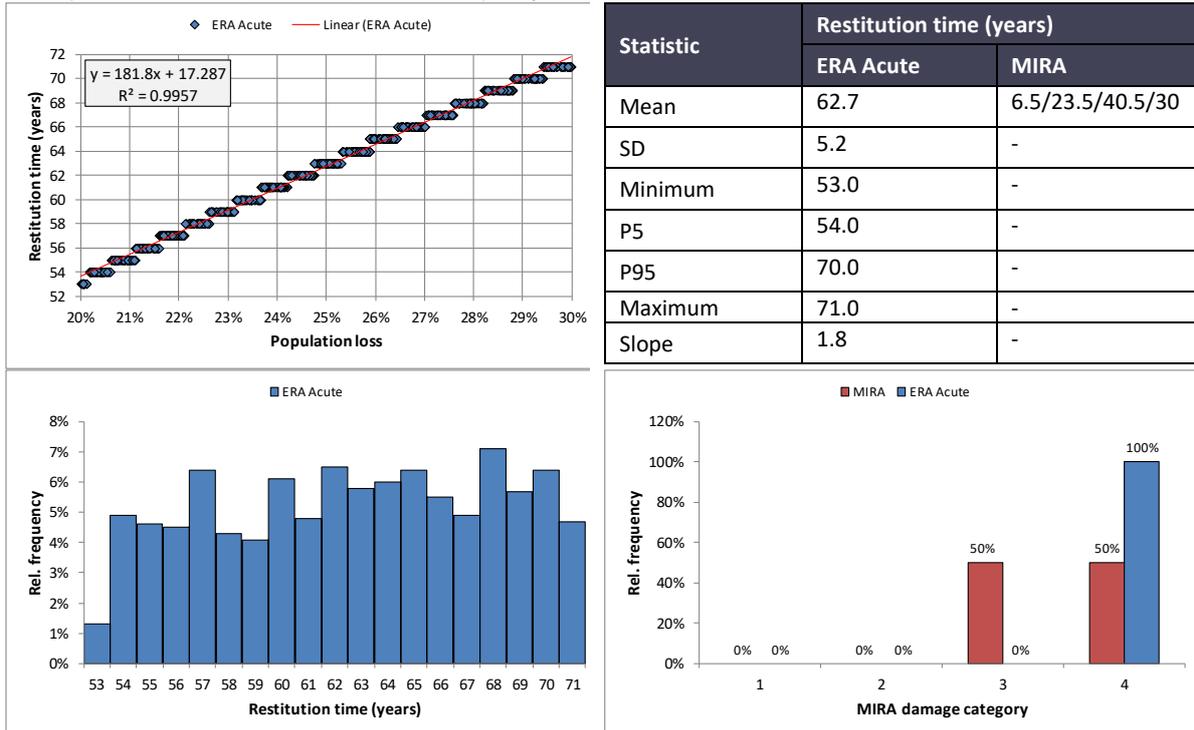


Figure 74. Estimated restitution time for population loss between 20 and 30%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 1-year categories (bottom right) and MIRA damage categories (bottom right).

WG7 (toothed whales, sea cows, sea turtles): Population loss 30-99%

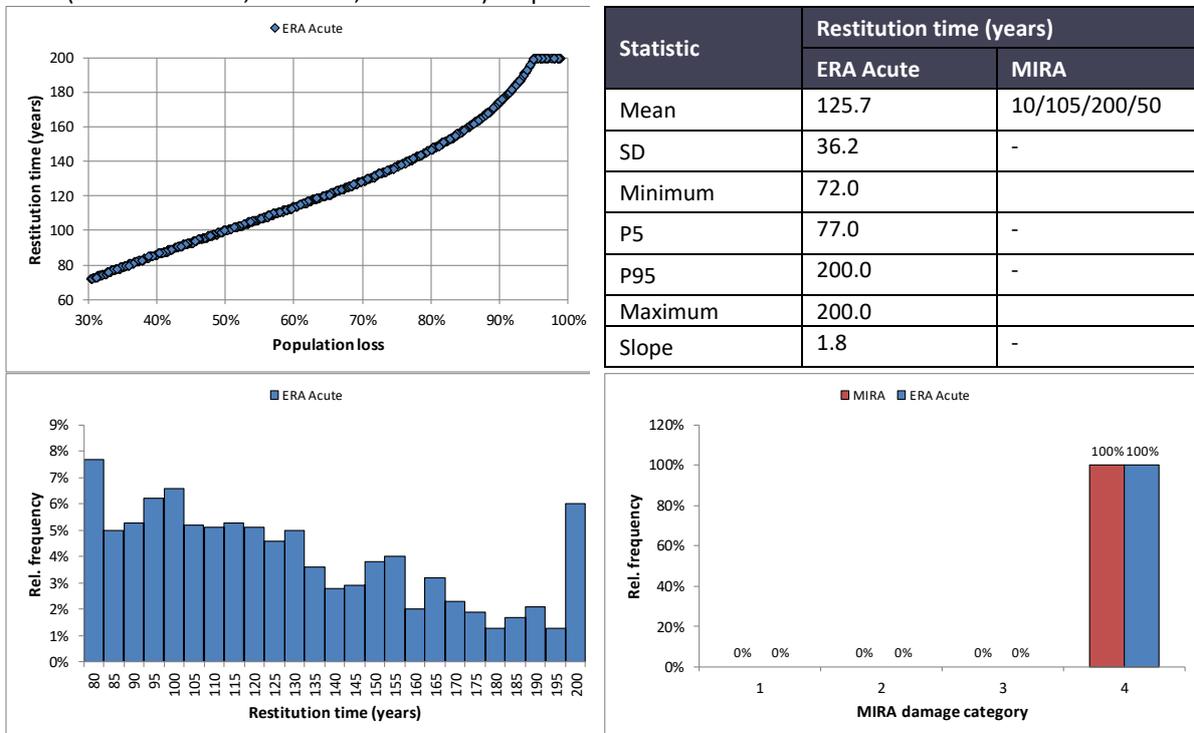


Figure 75. Estimated restitution time for population loss between 30 and 99%. Relationship between restitution time and population loss (upper left) with descriptive statistics (upper right). The slope is the effect of 1% population loss in the selected interval estimated from the linear equation. Classification of the estimated restitution intervals in 5-years categories (bottom right) and MIRA damage categories (bottom right).

The shoreline compartment

This section is concerned with the sensitivity and uncertainty testing of the shoreline compartment model of ERA Acute.

The resource unit (N) for shoreline is “km coastline” for specified habitat types. The shoreline habitats are classified according to the Environmental Sensitivity Index (ESI) classification system (Table 14). The shoreline habitat types are ranked from 1 to 10 corresponding to their sensitivity towards spilled oil (cf. Brude et al., 2015 for details).

Table 14. Environmental Sensitivity Index (ESI) for shoreline habitat types. Lower rankings represent shorelines that are less susceptible to damage by oiling; shoreline with higher rankings are more likely to experience damage by oiling.

ESI	Description of ESI category
ESI1	Exposed rocky shores, exposed, solid man-made structures, exposed rocky cliffs with boulder talus base
ESI2	Exposed wave-cut platforms in bedrock, mud, or clay, exposed wave-cut platforms in bedrock, mud, or clay Exposed scarps and steep slopes in clay
ESI3	Fine to medium-grained sand beaches, scarps and steep slopes in sand, tundra cliffs
ESI4	Coarse-grained sand beaches
ESI5	Mixed sand and gravel beaches
ESI6	Gravel beaches, riprap (cobble and boulders)
ESI7	Exposed tidal flats
ESI8	Sheltered scarps in bedrock, mud, or clay, sheltered riprap, sheltered rocky rubble shores, peat shorelines
ESI9	Sheltered tidal flats, vegetated low banks, hypersaline tidal flats
ESI10ABC	Salt- and brackish-water marshes, freshwater marshes, swamps
ESI10DE	Scrub-shrub wetlands, mangroves, Inundated low-lying tundra

Impact is directly related to the number of grid cells with oil thickness above a thickness threshold and the length of the shoreline in the grid cells. It is calculated by the following equation:

$$Imp_r = \sum_{cell} (L_r | T_r \geq TH) \tag{4.3}$$

Where L_r is the length of the shoreline for a given habitat type (r), T is the oil thickness and TH and thickness threshold. TH is defined as 1 mm for “flora” and 0.1 mm for “fauna”.

Oil thickness (T) is calculated by the following equation:

$$T_r (mm) = \frac{V(m^3)}{L_r (km) \times \frac{TR (m)}{\sin(\text{atan}(sl_r) \times PF)}} \tag{4.4}$$

Where V is the amount of accumulated oil in a grid cell, L is the length of the shoreline, TR is the tidal range, sl is the slope (°) and PF is a patchiness factor. The tidal range is given per grid cell and the slope and patchiness factor per shoreline habitat type (ESI). If the cell consists of several habitat

types (ESI) the accumulated amount of stranded oil is distributed according to their length and their oil holding capacity.

Three different distributions are used depending on the viscosity of the oil (Figure 76). If equal shoreline length, most of the stranded oil is allocated to ESI10 and ESI3. These shoreline types are also ascribed the smallest slope in the look-up table, which further increase the estimated oil thickness (cf. Eq. 4.4 and analysis below).

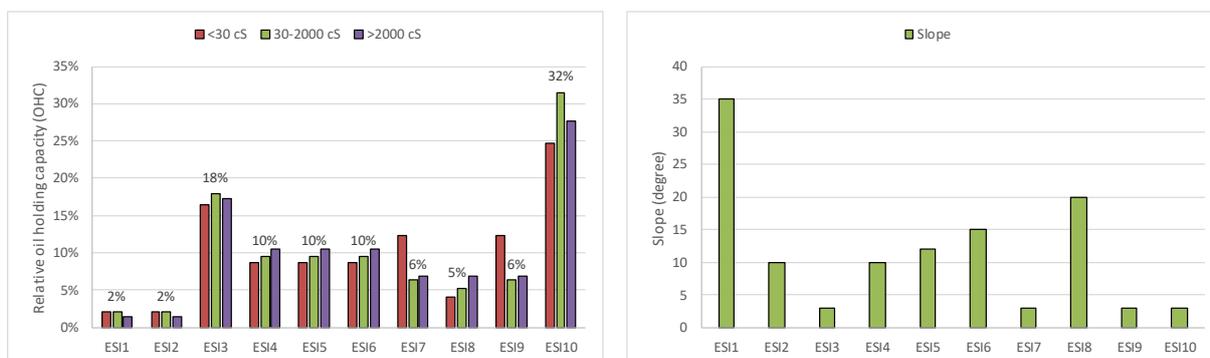


Figure 76. Relative distribution of stranded oil according to the relative oil holding capacity per ESI shoreline types (left) and the slope used for the different ESI shoreline types (right).

5 Uncertainty and sensitivity analysis

The base values and the probability distribution of the model input data used in the deterministic and stochastic uncertainty and sensitivity analyses are presented in Table 15. The base values used in the deterministic analyses are chosen so that the investigated range ($\pm 100\%$) cover the range of the parameter values in the look-up tables and the values in the Norwegian coastal resource dataset, except the shoreline length and stranded mass.

The shoreline length is set to 14 km (the diagonal of a grid cell), which is close to the mean ESI length per grid cell in the resource dataset (13.3 ± 18.6). The base value for stranded amount of oil is set to 27 m^3 , yielding an oil film thickness of 1 mm (when substituting the base values into Equation 5.4). Note that changing the base values have no influence on the relative relationship between the model output and model input data.

For the stochastic analyses, each parameter investigated has been assigned a probability distribution based on different goodness of fit tests and expert judgment. The Norwegian coastal dataset was used to find the best statistical distributions for the parameters as described below.

Table 15. Variation in the model parameter tested. Illustration of the distribution is illustrated in Figure 79.

Parameter	Base value	Range			Distribution
		Parameter 1	Parameter 2	Parameter 3	
Tidal range (m)	2.1	2.45	0.25	-	Normal
Slope (°)	20	3.03	10.15	34.72	Triangular
Patchiness factor	0.3	0.11	0.51	-	Uniform
Stranded mass (m^3)	27	-	-	-	Fixed values
Shoreline length (km)	14	-	-	-	Fixed values

Tidal range (TR): The tidal range model parameter was assigned a normal distribution. The distribution is based on different goodness of fit tests of tidal range for selected parts of the Norwegian coast (ESI_Norway.xlsx). The selected part used in the analyses gives a mean tidal range of 2.5 meter with a minimum of 1.5 meter and a maximum of 3.4 meters, and thus covering a large part of the Norwegian coastline.

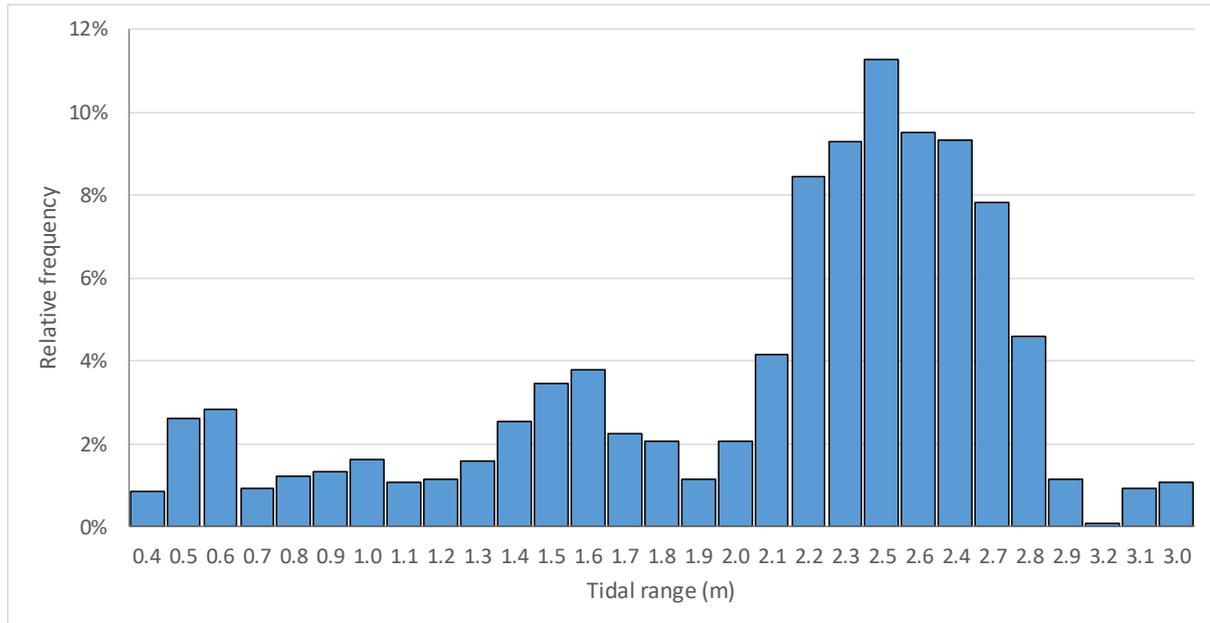


Figure 77. Histogram of tidal values from the shoreline resource dataset for the whole Norwegian coast. The histogram suggest that the dataset may be divided into three or four normal distributions.

Slope (sl): The slope model parameter was assigned a triangular distribution with a minimum value of 3°, a most likely value of 10° and a maximum value of 35°. The distribution is based on the recommended model slope values per ESI-shoreline type (cf. Table 9 and Figure 4 in Brude et al., 2015) and the resource dataset for the Norwegian coast (Figure 78). The true beach slopes along the Norwegian coast varies considerably more than the ERA acute model values. The ERA acute model values in Figure 78 are here considered to be single discrete values selected from a continuous triangular distributions of true slope values. This fills in the gaps (“missing data”) between the ESO specific slope values (cf. Figure 79).

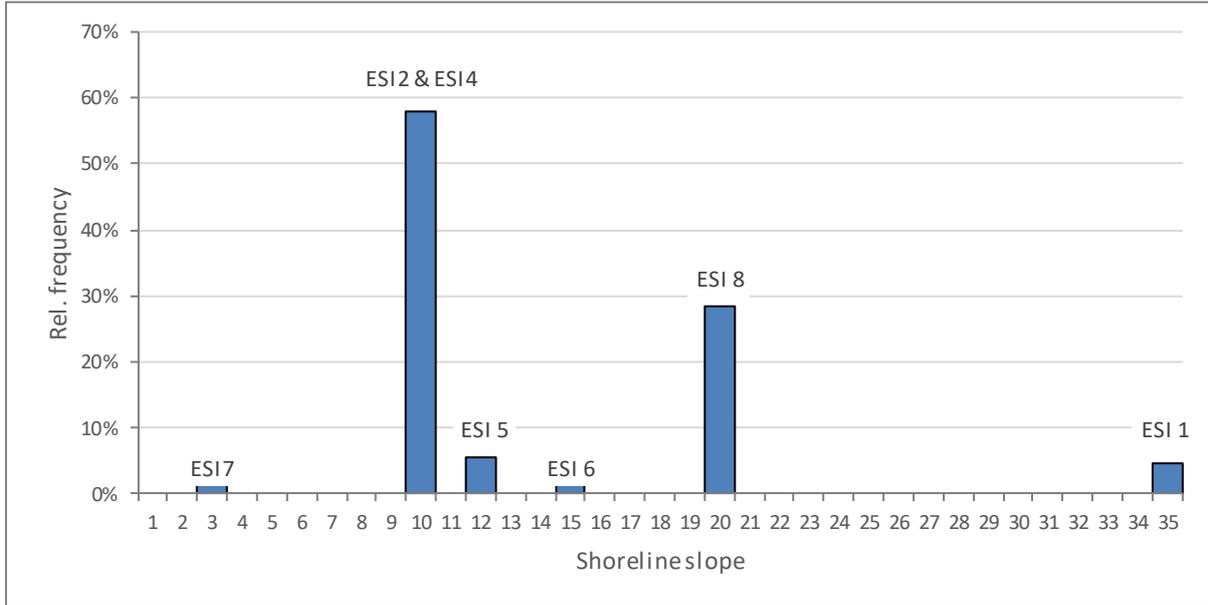


Figure 78. The slope values used in the Norwegian coastal dataset.

Patchiness factor (PF): The patchiness factor was assigned a uniform distribution with a minimum values of 0.13 and a maximum value of 0.51 (cf. Brude et al., 2015 for rationale). A uniform distribution is used as little is known about the uncertainty to this parameter (a uniform distribution means that all values within the defined range have equal probability).

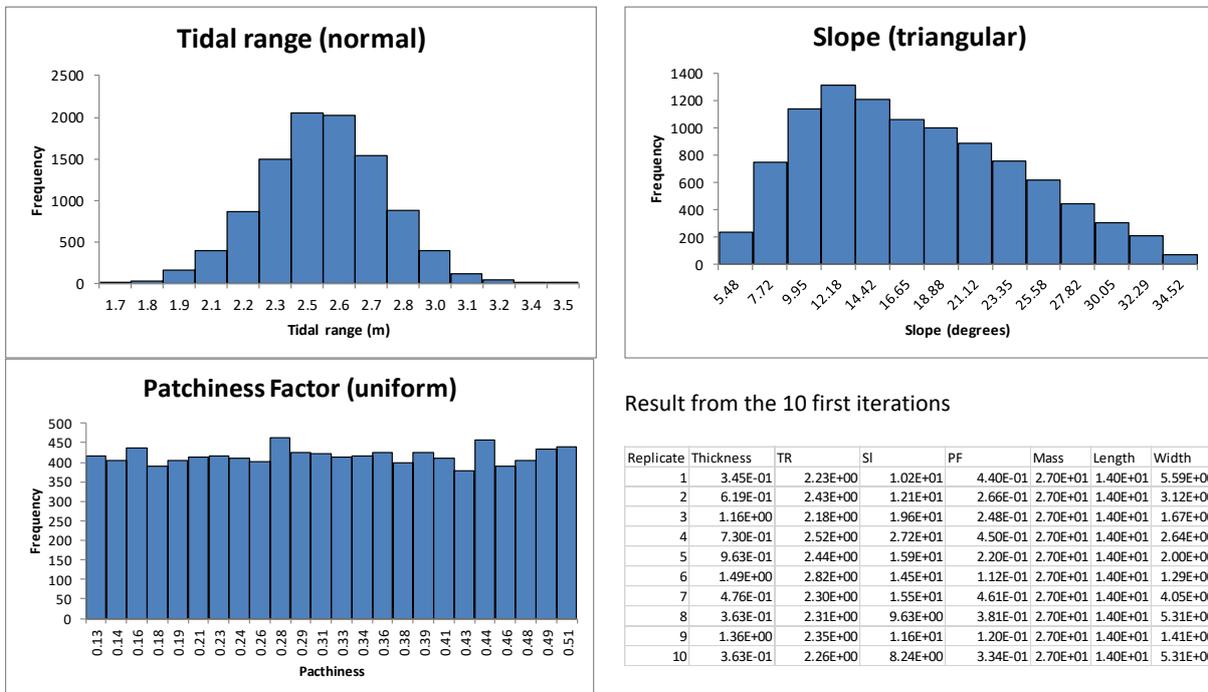


Figure 79. Probability distributions used in the stochastic uncertainty and sensitivity analyses. The labels show the upper limit of the interval (bin). The diagrams are constructed by drawing 10,000 random numbers according to the probability distribution defined in Table 15.

5.1 Deterministic sensitivity analysis

The analyses are carried out by varying one parameter at a time from a base value and investigating the effect on the model output, while the other model input data are held constant at their base value (cf. Table 15). The most important input parameters are identified by the vertical width and the slope of the curves.

The tidal range, shoreline length and the patchiness factor have largest effect on the oil film thickness within the uncertainty range tested. The curve is exponential and as expected lowering the value of the input parameters increases the oil film thickness (Figure 80). The stranded mass and shoreline slope have a linear effect on the oil film thickness. Increasing the stranded oil mass and the slope (i.e. decreasing the width) increases the oil film thickness (Figure 80).

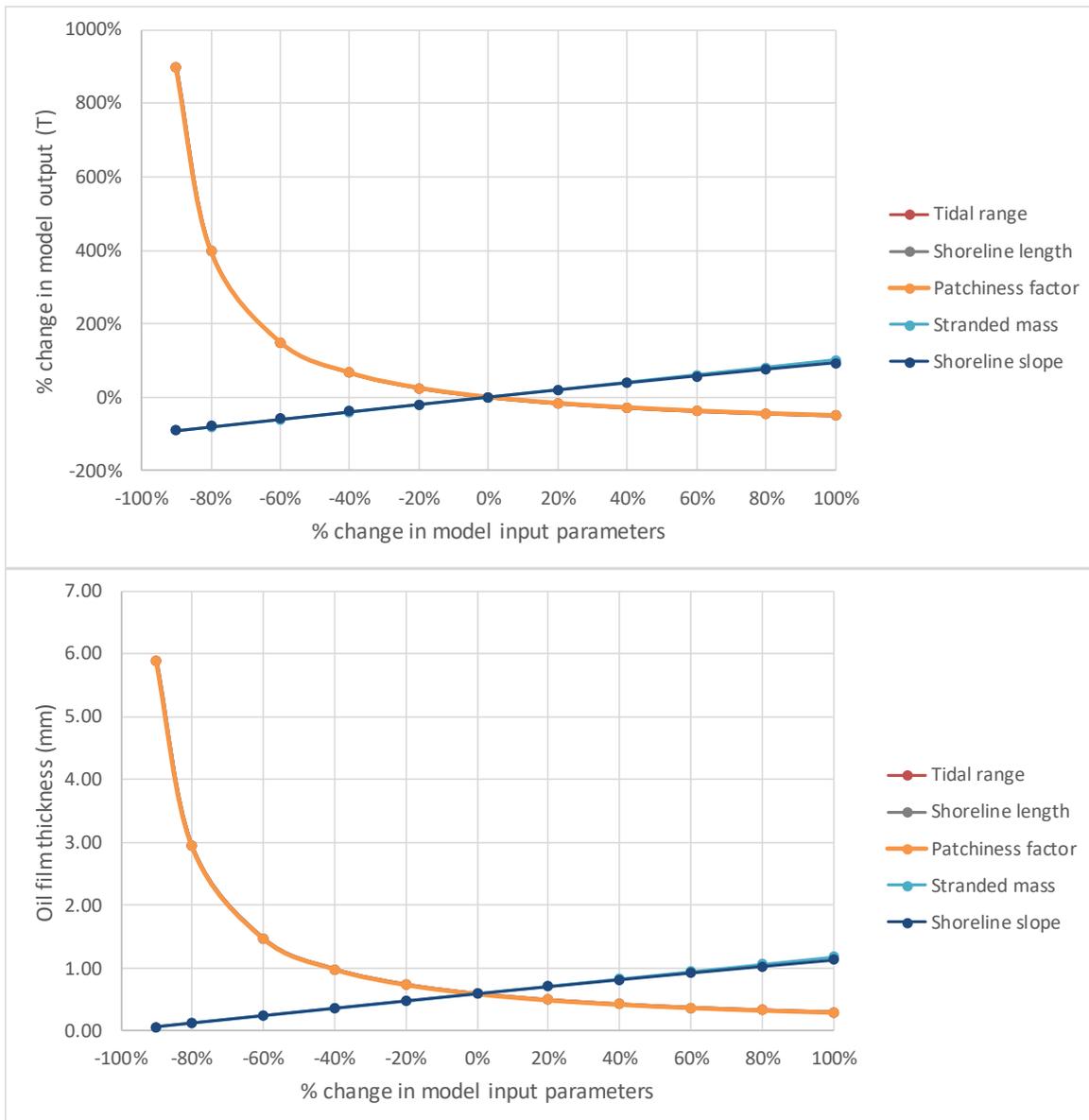


Figure 80. A spider graph comparing the effects on the five model input parameters on the model output results (oil film thickness). For each input the percentage changes in its value for the base case is plotted on the x-axis and the percentage (top) and absolute (bottom) change in results is plotted on the y-axis. Note that tidal range, shoreline length and the patchiness have identical curves and is plotted on top of each other.

5.2 Stochastic uncertainty and sensitivity analyses

A stochastic uncertainty and sensitivity analysis is performed to investigate the relative importance of the model parameters slope (sl), tidal range (TR) and patchiness factor (PF) on the model endpoint oil film thickness (T).

The results from the Monte Carlo Simulation (n = 10,000) is presented in Figure 81. The figure shows relative frequency (probabilities of the possible outcomes) for the oil film thickness as a result of the variation in the input variables. The pattern resembles an inverse Gaussian or truncated log-normal distribution. The mean oil film thickness is 0.80 mm with a subjective confidence interval of 0.21 to 2.25. Approximately 25% of the simulations would give an oil thickness above the threshold thickness for vegetation (flora).

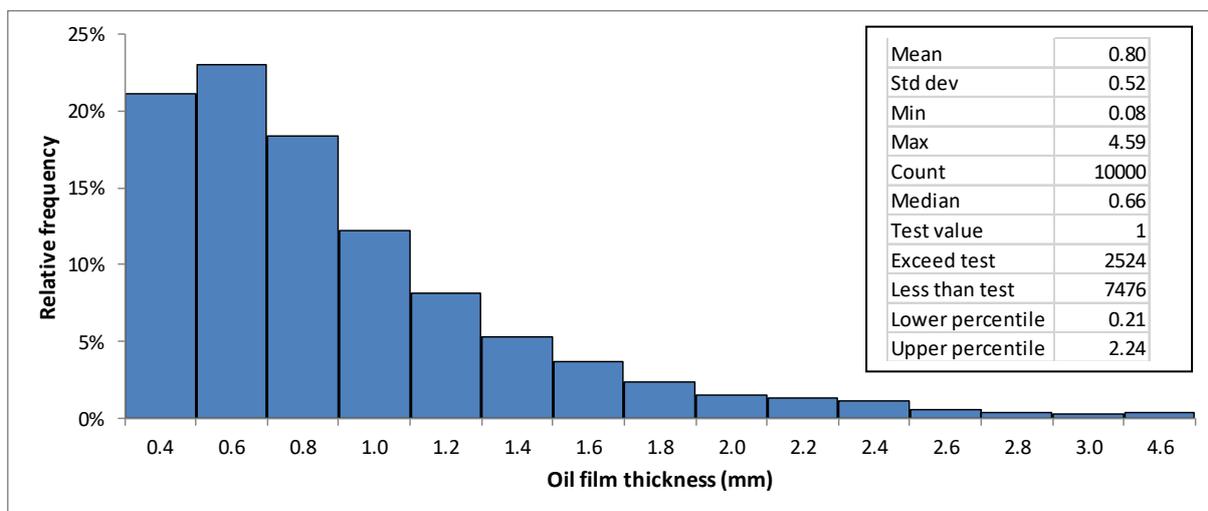


Figure 81. Histogram of the endpoint (oil film thickness) given the uncertainty range in the input parameters. Selected statistics is illustrated in a table.

The result from the sensitivity analyses are presented in Figure 82. The result from the Spearman correlation coefficient analysis is presented with p-values and importance rank. The pie diagram shows the sensitivity index from the Factor Prioritization by Reduction of Variance.

The slope and the patchiness factor are the two most important parameters, explaining 44% and 53% of the variation in the estimated oil film thickness range when both the shoreline length and stranded mass volume is held constant. Varying the stranded mass from 1 – 100 m³ reduces the relative importance, measured by the sensitivity index of the slope and patchiness factor to 22% and 27%, respectively.

Parameter	Volume: 27 m ³			Volume: 1- 100 m ³		
	Spearman Corr. Coeff.	p-values	Importance rank	Spearman Corr. Coeff.	p-values	Importance rank
Slope (sl)	0.69	0	Slope	0.42	0	Mass (m ³)
Tidal range (TR)	-0.14	0	Patchiness factor (PF)	-0.43	0	Patchiness factor (PF)
Patchiness factor (PF)	-0.69	0	Tidal range (TR)	-0.09	0	Slope
Mass (m ³)	-	-	-	0.75	0	Tidal range (TR)

Fixed volume (27m³)

Volume 1- 100 m³

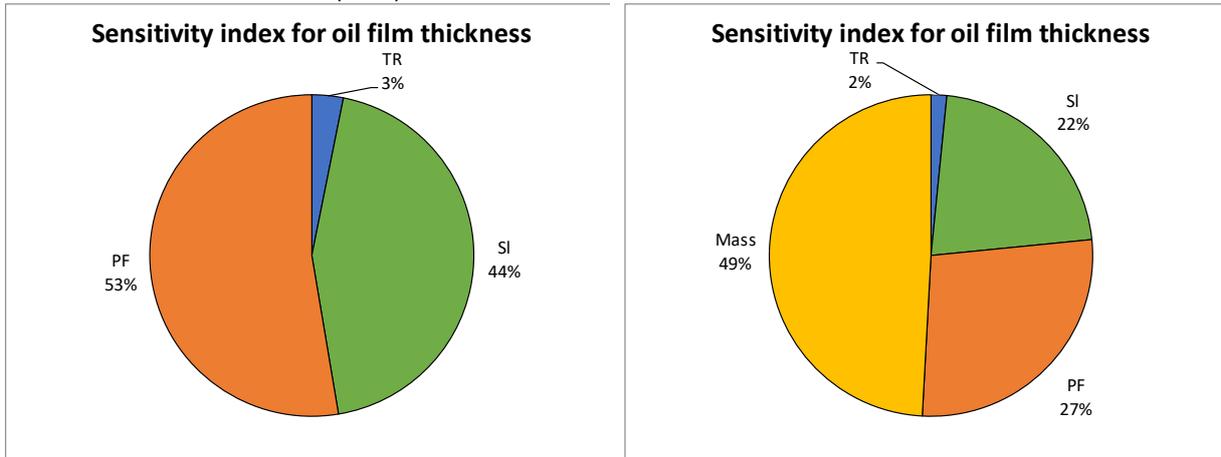


Figure 82. Result for the sensitivity analysis of T for accumulated stranded volume of 27 m³ and between 1- 100 m³ assigned a uniform distribution. See text for the range and probability distribution used for the other parameters: The length of the coastline is held constant at 14 km.

The water column compartment

This section is concerned with the sensitivity and uncertainty testing of the water column compartment model of ERA Acute.

6 The population model

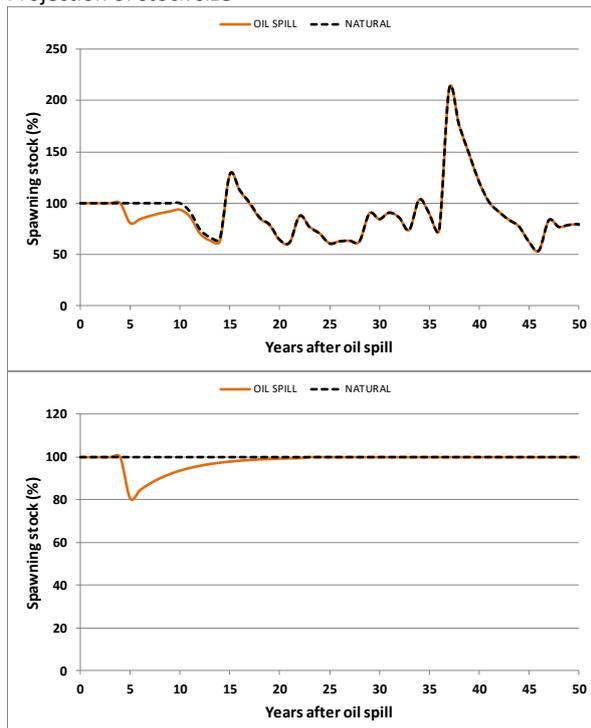
The global fish restitution model is programmed in Visual Basic and runs via a macro in Microsoft Excel. An algorithm programming guide is found in Appendix C in the water column report (Brønner et al., 2015). The model allows the user to include stochastic effects of climate (favourable, unfavourable and shifts) as well as different fishing pressure (added mortality for juvenile and/or adults) when calculating the restitution time. The model input is percentage larvae loss (calculated in previous step) and five life history parameters summarized in Table 16 for “long-lived” (represented by Barents Sea cod) and “short-lived” (represented by capelin) species (see Brønner et al., 2015 for details).

The model is run twice, one without (“natural”) and one with mortality caused by oil drift (and if selected with fishing mortality) resulting in a projection of future stock size without mortality due to oiling (and fishing) and a projection of the stock size with the effect of oiling (and fishing) mortality. The restitution time is defined when the affected stock is within 1% of the projected stock size without effect of oiling (and fishing) mortality. If the effect of climate (favourable, unfavourable and shifts) is included, the future population size will fluctuate randomly around this 'average' population size (or structure).

Table 16. Model input data, percentage larvae loss, for the two fish models “long-lived” and “short-lived” (from Brønner et al., 2015)

Parameter	Long-lived species	Short-lived species
Annual natural mortality of immatures (%)	20	40
Annual natural mortality of matures (%)	20	40
Age at recruitment (year)	3	1
Age at first spawning (year)	8	5
Maximum age (year)	25	5

Projection of stock size



Stock (population) loss

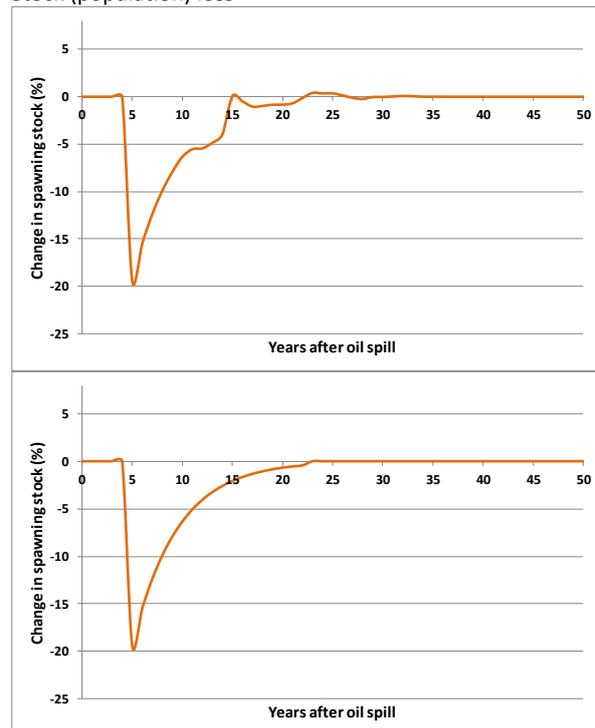


Figure 83. Illustration of the projection and population loss for long-lived species after an oil spill using stochastic (upper panel) and deterministic (lower panels) modelling. The egg and larvae mortality were 95%, the critical stock density 5% and the critical mortality was 90%, and the life history parameters for long-lived species as listed in Table 16. The restitution time is 11 (stochastic, i.e. climate = 1) and 14 years (deterministic, i.e. climate = 0), using 99% of the projected, undisturbed state as restitution threshold.

6.1 The gate model

Two fundamental input parameters in the model are the *critical density* and the *critical oil mortality*. The recommended (default) value for the two parameters are 5% and 99%, respectively for all species. The values are derived from extensive historical records, ecology and biology of fish larvae (match-mismatch hypothesis) and literature review (see Brönner et al., 2015 for details).

Critical density:

- If the analysed fish stock > Critical density, the model calculates the expected recruitment as the long-term average recruitment, i.e. recruitment is fully independent of the size of the spawning stock.
- If the analysed fish stock < Critical density, the model calculates the expected recruitment as the long-term average recruitment, multiplied by the current biomass divided by the critical density of the long-term average spawning stock.

Critical oil mortality:

- If percentage larvae loss > Critical oil mortality, the model calculates impact from a proportionate relationship between oil-induced mortality of larvae, and reduced recruitment (“one lost larvae results in one lost recruit”). If, for example, Critical oil mortality is set to 30%, any oil-induced impact on eggs and larvae >30% will reduce recruitment with the same percentage.

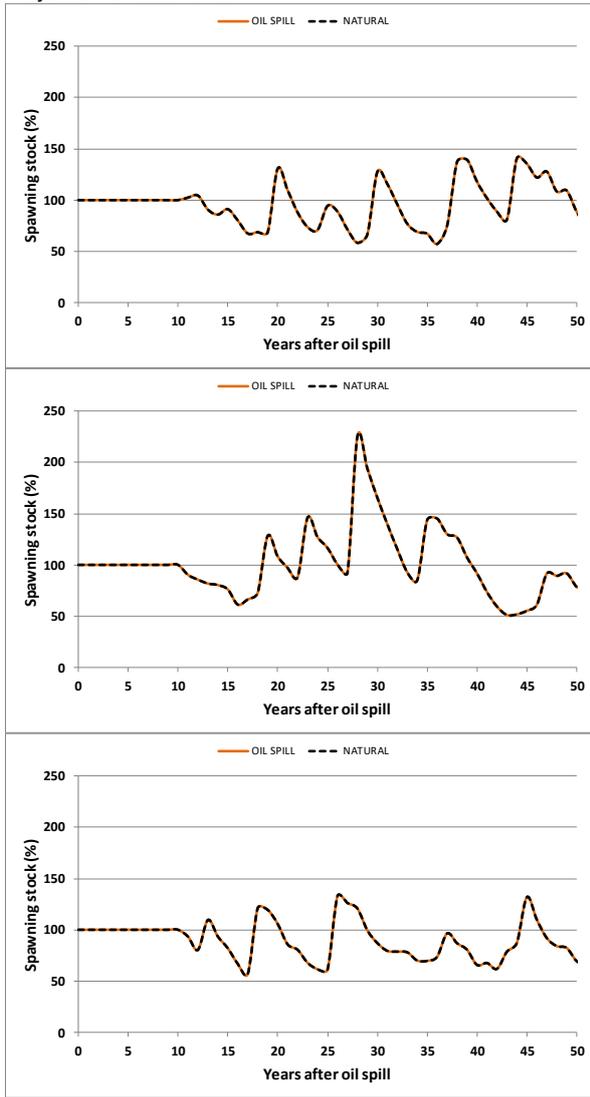
- If percentage larvae loss < Critical oil mortality, the model calculates impact using the *gate model*, i.e. using modelled natural survival up until recruitment as a reference level against which oil impact on eggs and larvae is measured.

The parameter Critical oil mortality represents a user option for impact modelling as in “MIRA” or using a more scientifically relevant approach.

To test the gate model, the fish population model was run with percentage larvae losses from 0.99%, i.e. less than or equal to the default critical oil mortality value of 99%. The results from three random stochastic (Climate = 1) and deterministic (Climate = 0) runs are illustrated in Figure 84 and Figure 85, respectively. The projected population sizes with and without oil are identical and thus none of the oil spills (egg/larvae losses) have measurable impact on the spawning stock. This is as expected using the gate model, and the rationale is that the overall natural mortality from the egg stage and up until recruitment is significantly higher than 99% (cf. Brönner et al., 2015).

Since it is difficult to imagine real situations resulting in higher fish egg/larvae mortality than 99%, one may conclude that oil spills will not cause any measurable effect on the population level for fish using the gate model with a critical oil mortality value of 99%.

Projection of stock size



Stock (population) loss

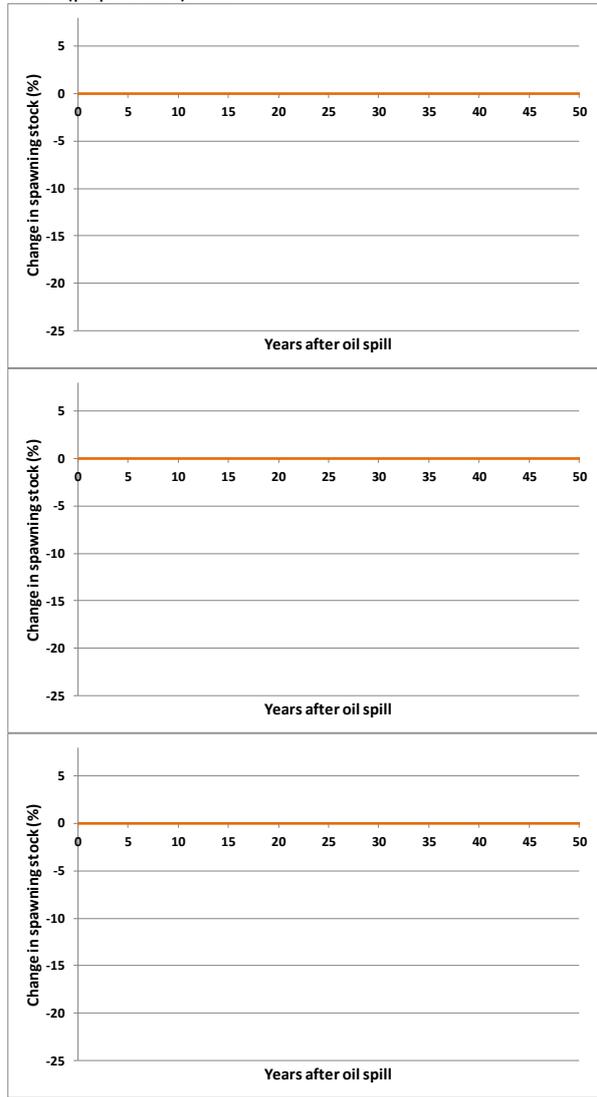
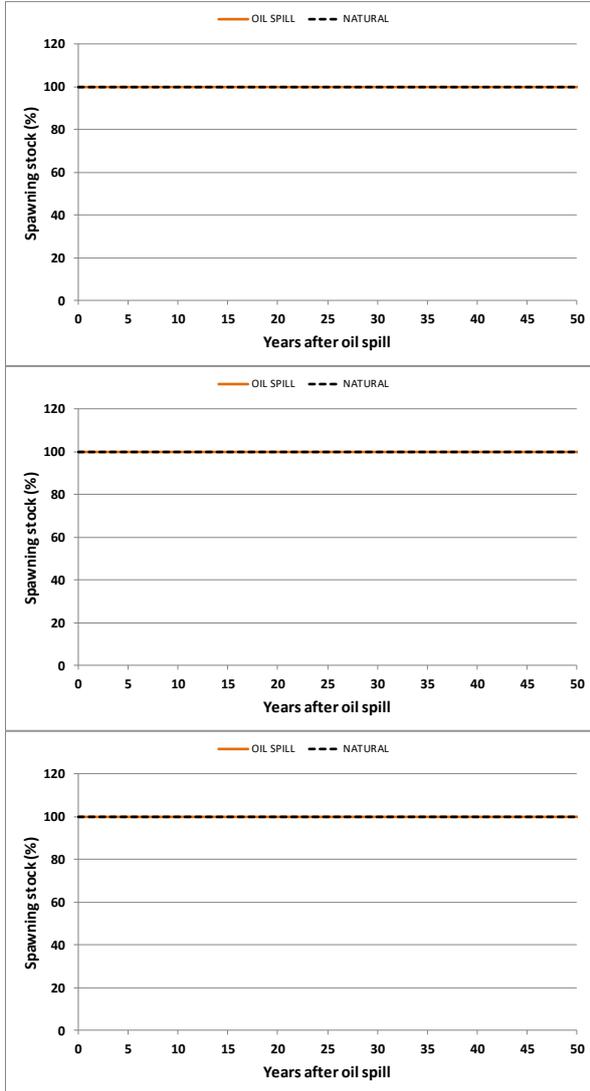


Figure 84. Three examples of stochastic modelling using the gate model for larvae loss ranging from 0-99%. All input parameters are set to recommended (default) values, i.e. the critical stock density is 5% and the critical mortality is 99%, and the life history parameters for long-lived species as listed in Table 16.

Projection of stock size



Stock (population) loss

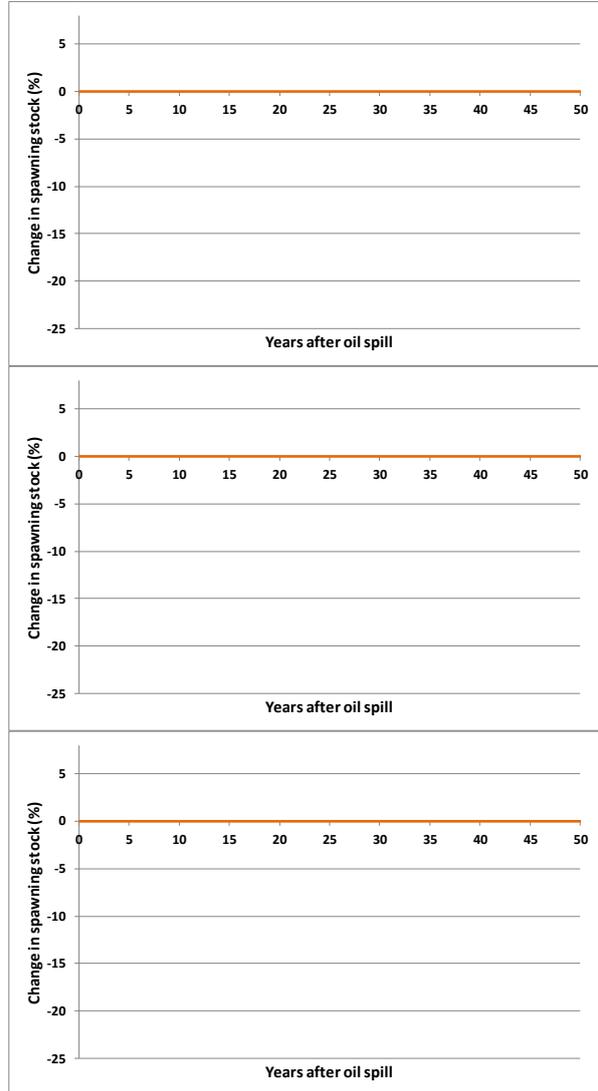


Figure 85. Three examples of deterministic modelling using the gate model for larvae loss ranging from 0-99%. All input parameters are set to recommended (default) values, i.e. the critical stock density is 5% and the critical mortality is 99%, and the life history parameters for long-lived species as listed in Table 16.

The fish model projects the future population size with and without oil mortality. This is a desired feature when estimating the restitution time caused by oil spills. The effect may be seen in the example in Figure 83 (left panels), where unfavourable climate conditions (little inflow of warm water) approximately 10 years after the oil spill causes a decrease in the “both” projected spawning stocks (natural and oil spill). The affected stock is less influenced and is within 99% of the unaffected stock in year 15, resulting in a restitution time of 11 years. For the deterministic modelling the unaffected stock size is fixed at 100% and the affected stock reaches the 99% threshold after 14 years.

Table 17 gives an overview of restitution times estimated from 30 deterministic (climate = off) and stochastic (climate = on) simulations of the population model using a Critical oil mortality less than

the egg/larvae loss (“one lost larvae = one lost recruit”). In the deterministic run the natural population size is constant while in the stochastic it is affected by climate.

The estimated restitution time only differs for relative large larvae losses, where the estimated restitution time range for 7 to 9 years. In a deterministic analysis the result will be the same for each simulation.

Table 17. Estimated restitution time estimated for 30 stochastic (Stoch) and deterministic (Deter) simulations.

Sim. No	Egg/larva: 5%		Egg/larva loss: 10%		Egg/larva: loss: 15%		Egg/larva: loss: 20%	
	Stoch.	Deter.	Stoch.	Deter.	Stoch.	Deter.	Stoch.	Deter.
1	1	1	4	4	6	6	8	7
2	1	1	4	4	6	6	7	7
3	1	1	4	4	6	6	7	7
4	1	1	4	4	6	6	8	7
5	1	1	4	4	6	6	7	7
6	1	1	4	4	6	6	6	7
7	1	1	4	4	6	6	8	7
8	1	1	4	4	6	6	8	7
9	1	1	4	4	6	6	8	7
10	1	1	4	4	6	6	8	7
11	1	1	4	4	6	6	6	7
12	1	1	4	4	6	6	8	7
13	1	1	4	4	6	6	6	7
14	1	1	4	4	6	6	6	7
15	1	1	4	4	6	6	8	7
16	1	1	4	4	6	6	7	7
17	1	1	4	4	6	6	7	7
18	1	1	4	4	6	6	8	7
19	1	1	4	4	6	6	7	7
20	1	1	4	4	6	6	6	7
21	1	1	4	4	6	6	8	7
22	1	1	4	4	6	6	8	7
23	1	1	4	4	6	6	9	7
24	1	1	4	4	6	6	8	7
25	1	1	4	4	6	6	6	7
26	1	1	4	4	6	6	8	7
27	1	1	4	4	6	6	6	7
28	1	1	4	4	6	6	6	7
29	1	1	4	4	6	6	8	7
30	1	1	4	4	6	6	7	7
Mean	1.0	1.0	4.0	4.0	6.0	6.0	7.3	7.0
SD	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.0

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