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Assessing Environmental Risk of Oil Spills with ERA Acute

A New Methodology

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Preface

This book provides an introduction to the ERA Acute methodology for acute oil spills. The methodology has been developed using recent research in the field of oil spill, establishing a globally applicable environmental risk assessment (ERA) methodology for accidental discharges. ERA Acute will also be implemented as the new ERA methodology for the Norwegian Continental Shelf.

The general methodology framework and overall compartment descriptions with the main equations are outlined in this book which is aimed at giving the reader an introduction to the subject. The full description of the methodology algorithms and the reasoning behind them are described in the project reports provided as open access online documents (see references to each report in each chapter). A user-friendly software tool is developed for use of the ERA Acute methodology. Please be aware that while the authors are publishing this method for open use, this publication is provided "as is" and all use of the published method will be at the user's own risk and cost. The authors make no representations or warranties as regards the method, effectiveness, safety, fitness for a particular use or purpose or non-infringement of any intellectual property rights and shall not be liable for anyone's use of the method and encourage all potential users of the method to assess for themselves whether and how the published method should be applied for their use.

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About This Book

This short book starts with an overview and general information and then provides more technical details through the following chapters.

Chapter 1 "Introduction to the concepts" is aimed at readers who wish to get an overview of the ERA methodology and concepts, and why the method was developed. This chapter also provides a brief introductory summary of potential areas of use, and a brief discussion of some of the uncertainties involved when introducing a new methodology. These two latter topics are covered in more depth in Chaps. 2 and 4, respectively, for the interested reader.

The second part, Chap. 2, "Environmental Risk Management Applications of ERA Acute" should be read by those interested to learn more about what the ERA Acute methodology can be used for, how it can be used for different analysis purposes and how the endpoints can be presented.

The third part, Chap. 3, "An ERA Acute Model Overview" is relevant to those who want to go deeper into the basic equations and the model concepts. For even more detail and background knowledge, the reader is encouraged to consult the background reports which are made available (see the links in the references to the chapters). These background reports also contain original references to peer-reviewed work describing the methodology in more detail than could be included in a short book.

The fourth part consists of two chapters which should be read by those who are interested in the documentation of the methods used for testing and validating ERA Acute for use as a risk assessment method as well as the uncertainty handling. Chapter 4 "Testing and Validating against Historic Spills" describes the process and challenges of comparing ERA Acute against two historic spills, the Deepwater Horizon and Exxon Valdez oil spills. Uncertainty handling based on sensitivity testing is described in Chap. 5, "Handling Uncertainty and Sensitivity of ERA Acute towards Input Parameters". Background reports are available for these studies as well for the interested reader.

Tables including supplemental information and references are provided at the end. Abbreviations used are defined the first time they are used in this book, and not in each chapter.

Contents

Abbreviations

ALARP	As Low As Reasonably Possible
BCF	Bioconcentration Factor
CBR	Critical Body Residue
DHOS	Deepwater Horizon Oil Spill
DSHA	Defined Situation of Hazard and Accident
ELS	Early Life Stage
EqP	Equilibrium Partitioning Theory
ERA	Environmental Risk Assessment
ERM	Environmental Risk Management
ESI	Environmental Sensitivity Index
EVOS	Exxon Valdez Oil Spill
FPRV	Factor Prioritization by Reduction of Variance
GIS	Geographical Information System
IW	Interstitial water
MC	Monte Carlo
MIRA	An ERA method used on the NCS
NCS	Norwegian Continental Shelf
NEBA	Net Environmental Benefit Analysis
NRDA	Natural Resources Damage Assessment
O&G	Oil & Gas
OHC	Oil-holding capacity
OSCAR	Oil Spill Contingency And Response (Oil spill trajectory model by SINTEF)
OSRA	Oil Spill Risk Assessment
OVI	Oil Vulnerability Index
PRCC	Partial Rank Correlation Coefficient
QSAR	Quantitative Structure Activity Relationship
RDF	Resource Damage Factor
RTC	Risk Tolerance Criteria
SA	Sensitivity Analysis

SCAT	Shoreline Cleanup Assessment Technique
SIMA	Spill Impact Mitigation Assessment
SSD	Species Sensitivity Distribution
THC	Total Hydrocarbon
TOC	Total Organic Carbon
VEC	Valued Ecosystem Component
WC	Water column

Chapter 1
Introduction to the Concepts and Use of ERA Acute

Abstract Introducing the main concepts of ERA Acute, this chapter describes the overall framework and purpose of the methodology. ERA Acute is a recently developed oil spill risk assessment (OSRA) methodology for quantification of oil spill impacts and risk (Environmental Risk Assessment, ERA). It covers four environmental compartments; sea surface (seabirds, turtles, marine mammals), water column (fish eggs/larvae), shoreline and seafloor (species and habitats) using continuous impact functions and introduces the Resource Damage Factor (RDF). The methodology depends on external oil spill modelling and input data related to the presence and vulnerability of Valued Ecosystem Components (VECs). ERA Acute is developed to provide an improvement over the currently used "MIRA" method on the Norwegian Continental Shelf (NCS) and is better suited for risk management, decision-making and analyses from screening studies to full environmental risk assessments.

Keywords ERA Acute concept · ERA Acute input data · Environmental compartments · Environmental risk assessment · Environmental risk management

1.1 Why the Need for a New Methodology?

Environmental Risk Assessments (ERAs) are a crucial part of planning and execution of offshore oil and gas (O&G) activities and are important in supporting the O&G industry in environmental risk management (ERM) of their operations worldwide. In varying regulatory frameworks, operators must ensure overall high environmental performance, whether it is in applications for permits, or in planning or operation of activities where there is a risk of an accidental oil spill. Quantitative ERAs of acute oil spills at different levels of detail are used to support decision-makers in complying with regulations, e.g. for activity applications and planning processes for oil spill response.

Several ERA models, assessing potential impact and risk from an acute oil spill, exist and are available for global use. A recent overview of some applicable models

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for risk assessments in the Arctic is given in Wenning et al. (2018). Some available models for use in a risk assessment process are oil spill trajectory models. The Bureau of Ocean Energy Management in the US uses "Oil Spill Risk Analysis Model" (OSRAM) which calculates probabilities of surface oiling at specific locations (Guillen et al. 2004, BOEM webpage for OSRAM). The "Blowout and Spill Occurrence Model" (BLOSOM) was developed by the U.S. Department of Energy's National Energy Technology Laboratory, and has e.g. been used to evaluate the coastal communities' vulnerability to oil spills in the Gulf of Mexico area from deepwater and ultra-deepwater blowouts (Nelson et al. 2015; NETL Factsheet 2019). Readily available also is the GNOME-model (General NOAA Operational Modeling Environment) by the US National Oceanographic and Atmospheric Administration. The OSCAR (Oil Spill Contingency and Response) model by SINTEF is frequently used on the Norwegian Continental Shelf (NCS). Also available is the MIKE model by DHI for surface and water column modelling. These oil spill trajectory models make use of Geographical Information Systems (GIS) to geographically locate areas of potential concern but may vary with respect to the number of environmental compartments they include. Several include response option modelling, e.g. GNOME and OSCAR. Taking it a step further, some established models include an impact assessment of potentially harmed Valued Ecosystem Components (VECs). The SIMAP model by RPS ASA has oil spill trajectory modelling integrated and is a coupled oil spill modelling and risk assessment by also including exposure and impact modelling to wildlife groups. Links to the home pages of the mentioned models are given in the reference section to this chapter.

On the NCS the quantitative "MIRA" method has been used as an industry standard since the 1990s (NOROG 2007), for execution of ERAs for Authority applications, planning and other pre-spill analyses. MIRA uses input of external oil spill fate and transport modelling, for example by using input from the OSCAR model, or similar trajectory models to calculate potential population losses of wildlife and impacted shoreline habitats. The industry and regulators in Norway have seeked an improvement over MIRA, and a model that could be globally applicable in line with "Guideline for oil spill risk assessment and response planning for offshore installations" (IPIECA-IOGP 2013). ERA Acute was developed to meet these requirements. Like MIRA, ERA Acute does not contain an integrated oil spill trajectory model but allows the user to select a preferred oil spill model giving the required input format. The methodology is expected to replace MIRA on the NCS following comprehensive testing, validation and a series of case studies comparing the two methods. The case studies are not described in this book. Like MIRA, ERA Acute uses the results of oil spill trajectory statistics, primarily aimed at assessments for pre-activity planning.

1.2 Methodology, Model and Software

The ERA Acute methodology provides updated impact and restoration functions based on available international research, both peer-reviewed papers and scientific reports. It is designed to have robust and continuous damage functions in four compartments, i.e. a harmonized framework of calculations, whilst maintaining scientific integrity of each compartment. ERA Acute does not include an oil spill trajectory model but utilizes input from any oil spill model that can provide results from a multitude of single simulations exported to a standardized grid format. VECs are natural resources, e.g. seabirds, shoreline habitats etc. for which impacts are calculated. The VEC input data are gridded to the same standardized format and each VEC is ascribed to the compartment where the main impact occurs.

The *methodology* of ERA Acute is an analytical concept which depends on input data from preceding models, which need to provide data of adequate quality. The ERA Acute *model* itself contains mathematical functions in a sequence that make up the impact and restoration calculations, and the methodology also has defined concepts related to the recommended presentation of the analytical endpoints of these calculations. A *software tool* has been developed to run the model calculations, with an interface to assist users in setting up the correct inputs, run the calculations and view the results. However, the software is not the focus of this book and the methodology can be used independently. The methodology, including the descriptions of use of input data are described in an *industry guideline* (NOROG 2020), whereas the biomathematical model functions and sequence of calculations are described as an overview in this book and in the underlying development reports (see list of references). As far as possible in this short book, we have included the equations.

Figure 1.1 shows an overview of the ERA Acute methodology and the division into: Inputs (top two boxes), model calculation units (middle box) and result presentation concepts (bottom box). The required input data on VECs and oil drift simulations are not included in the model nor included in the software tool (lilac background), offering a flexibility in choice of oil spill model and VEC data to be used in the risk assessment. Each of the impact and restoration calculations contain parameter values that are provided by the user as input files (see Sect. 1.4.3). For the parameter values, default values are available suitable for global use. These may be changed if specific knowledge exists about local resources (VECs) etc., thereby reducing uncertainty. The functions (middle light orange box) calculate impacts and restoration-related results and summarize and create statistical results. The functions and their sequences have been implemented in the software tool calculator. The software tool also includes interfaces for setup, calculation and presentation of recommended results (lower light orange box).

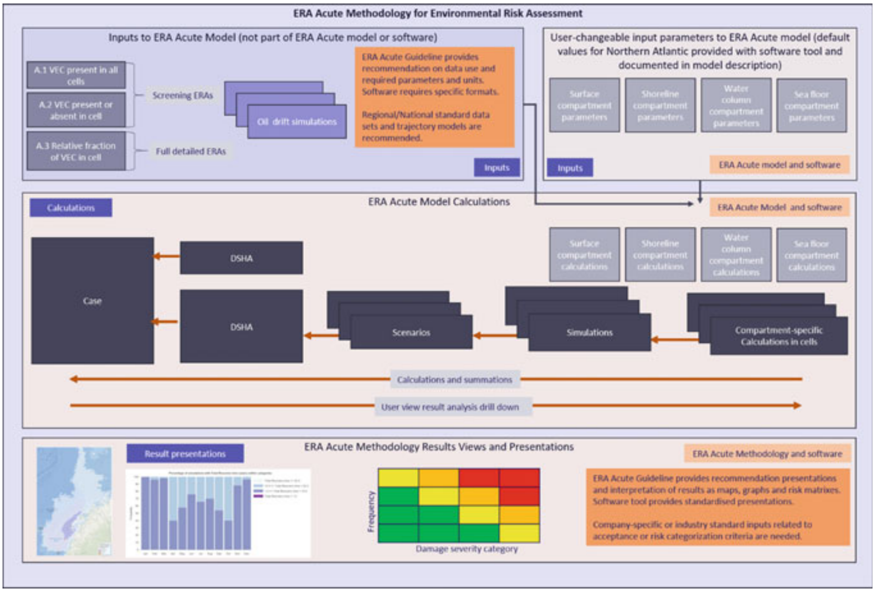

Fig. 1.1 The ERA Acute methodology showing the division into Inputs (top two boxes), model calculation units (middle box) and result presentation concepts (bottom box). Data on resources (VECs) and oil drift simulations are not included in the model (lilac background) whereas the ERA Acute conceptual model documentation includes recommended values for input parameters for each compartment (upper right light orange box), and the calculations (middle light orange box). The software includes setup, calculation and presentation (lower light orange box) tools. (DSHA—defined situation of hazard and accident)

1.3 Basic Concepts of ERA Acute

1.3.1 Four Compartments

ERA Acute uses gridded data on the biological distribution of a VEC (i.e. biological resources: species, communities or habitats) within the area of interest, in four environmental compartments mentioned above: Sea surface, shoreline, water column and seafloor. The VECs are assigned to the compartment where their impact occurs. Some VECs may occupy more than one compartment, for example representing resources in different life stages that have separate data sets. Whilst it was important to design a common framework for the ERA Acute methodology calculations, the different nature of the impact mechanisms is reflected in the risk functions of each of the four compartments. Emphasis has also been placed on keeping data transparency throughout the calculations.

1.3.2 ERA Acute Uses Continuous Risk Functions

Where category-based models like MIRA (NOROG 2007) assume a probability distribution of impacts in categories based on oil amount intervals, ERA Acute applies a continuous impact function based on the exposure, lethality given exposure and the VEC fraction present in the cell. The continuous impact and damage functions are believed to be more suitable for e.g. Net environmental benefit analysis (NEBA)/Spill Impact Mitigation Assessments (SIMAs) than category-based assessments, since more subtle differences in exposure will give different impact results which the risk assessor can then evaluate for decision making.

1.3.3 Two Main Steps—Three Levels of Detail

Questions to be answered by ERA-related studies vary in demand for detail, depending on e.g. the phase of the project, the maturity of petroleum activity in the region, or the sensitivity of the environment. The model framework is therefore designed to be flexible in its uses, and ERA Acute calculates several endpoints. Chapter 2 is dedicated to the application of ERA Acute results for environmental risk management purposes.

The modelling is carried out in two main steps. In the first step (A), ERA Acute methodology uses input from the oil spill trajectory model and the VEC data to calculate impact in each grid cell for each oil drift simulation (see Fig. 1.6). The results are summed up or averaged for each VEC in all compartments. In the second step (B), recovery results are calculated.

1.3.3.1 Impact Calculation (Step A)

Impact modelling in ERA Acute uses the framework of probability of exposure (p_{exp}), probability of lethal effect given exposure (p_{let}) and presence of vulnerable resources (VEC "unit") to calculate the mortality in each grid cell for each spill simulation. This basic principle is the same in all compartments, however the actual calculation of exposure and lethal effect, as well as the VEC "unit" in each compartment reflects the differences in mechanism of harmful action. The exposure and lethality parameters are determined from the compartment-specific oil spill impact parameters, such as oil coverage above a certain film thickness on the sea surface to induce a mortality to seabirds, turtles and marine mammals and oil mass on the shoreline to induce impact to sensitive shoreline types. ERA Acute uses continuous exposure-response relationships in order to predict mortality, meaning that a change in exposure from the oil drift will lead to a change in mortality as output. For species at the sea surface or in the water column compartment, the total injury is calculated for each spill simulation by summarizing the impact in all grid cells affected by the simulation.

This will give a total population loss of seabirds/mammals or fish larvae loss for each simulation. For the shoreline compartment, the impact is also summarized to a total shoreline impact in kilometers, distributed on the various shoreline rankings of Environmental Sensitivity Indexes (ESI) (NOAA 2002). Similarly, for the seafloor compartment, the total impact is given in km^2 impacted for each benthic habitat or community.

ERA Acute can use three levels of detail in the continuous-function impact calculations, depending on availability of data on VEC occurrence and distribution. Two screening levels allow for ERA Acute risk assessment even if VEC data are limited or even missing. Oil spill trajectory input data are needed at all levels, however, not all analyses may require complex modelled input of both oil and VEC. Simplified oil spill input data can be prepared manually for screening purposes or based on actual knowledge from a spill.

Impact calculation level A.1 is used if there are no data on the presence of environmental resources available (no VEC data). It uses only the oil drift simulations to determine exposure and potential mortality and assumes the most sensitive resource is present in all cells as a conservative estimate of the potential risk area. This quantitative result is suitable for identifying areas at risk in a screening or early phase project decision, or for identifying which area to focus on filling data gaps. It is particularly useful in areas where no knowledge exists on the presence of VECs, allowing ERA Acute to be used for screening purposes (see Sect. 2.3) or decision support where a specific detail on particular species is not needed (see Sect. 3.2.1). Parameters that relate to the sensitivity of the species are provided as default values based on globally applicable data, e g. global VEC wildlife groups.

Impact calculation levels A.2 and A.3 use resource data to identify specifically where impacts and risks to resources are highest. Level A.2, the second screening level, includes knowledge and data of whether the most sensitive VEC is present or not in the cell, thereby excluding cells with known non-presence of sensitive VEC (see Sect. 1.4.2.2). At the most detailed level (A.3), the full-resolution data on VEC abundance distributions are used (i.e. population fraction in each grid cell), providing a more accurate measure of potentially impacted fractions of the VEC (population loss, impacted coastline length or seafloor area). This is suitable for more detailed studies, e.g. analyses in sensitive areas, detailed decision making etc. and are used for further calculations in the next step, recovery time calculations (step B).

1.3.3.2 Recovery Estimation (Step B)

In the second main step (B), the duration of the impact (i.e. the total recovery time) is calculated as three time-factors for each VEC; the *impact time* (t_{imp}) describes the time until full impact is seen, *lag time* (t_{lag}) is the time before restoration can commence (where relevant), and *restoration time* (t_{res}) is the time it takes for the resource to recover from re-growth starts to pre-spill levels. For the four environmental compartments, different parameters and sub-models are used to calculate restoration times. The restoration time for birds and marine mammals is calculated based on the population loss using a discrete logistic growth model. For the water column, a global fish-population model has been built that translates the egg or larvae loss to a restoration time for the adult spawning stock biomass. The shoreline restoration calculations use a simpler look-up table to estimate the restoration time for a specific ESI shoreline type. Restoration time in soft seafloor substrates is calculated by a linear relationship between the amount of oil in the sediment above a threshold value and the expected maximum concentration of Total Hydrocarbon (THC) resulting from sedimentation of oil.

1.3.4 Introducing the Resource Damage Factor

ERA Acute introduces the Resource Damage Factor (RDF) as an index that combines the extent of impact and duration of impact described by the recovery time. RDF was previously denoted Resource Impact Factor (RIF) (Stephansen et al. 2017a, b; Spikkerud et al. 2006) but this was updated to better clarify that the concept includes both extent and duration of the impact in the damage assessment. In Fig. 1.2, RDF is illustrated by the geometric area representing the combination of extent (y-axis as loss) and duration (x-axis). Its calculation is slightly different in the four compartments (Chap. 3). The RDF supplements the recovery time as an endpoint of the damage assessment. Figure 1.2 illustrates impact as a fraction of the VEC lost (e.g. population loss) and the calculation of time factors and RDF.

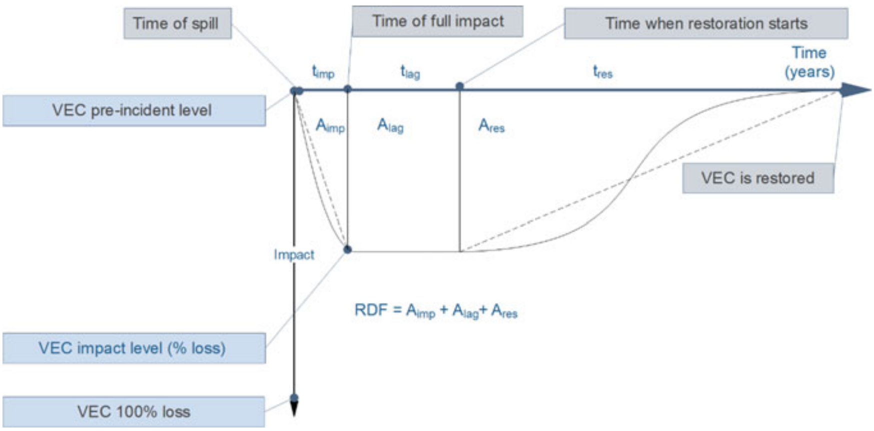

Fig. 1.2 Basic illustration of the use of impact as resource (VEC) loss and time factors to calculate the Resource Damage Factor as the geometric area representing the combination of extent and duration of impact

1.4 Inputs Needed for ERA Acute

1.4.1 Oil Spill Trajectory Modelling

ERA Acute does *not* include an oil spill trajectory model. Oil drift simulation models used should provide results from a multitude of single simulations exported to a standardized grid format. Each simulation has a start date and a duration, which is used to identify the relevant month. Each cell in each simulation has output values of the necessary oil inputs.

Although the ERA Acute project has used SINTEFs oil spill trajectory model Oil Spill Contingency And Response (OSCAR) as an example for development purposes, oil drift simulations are carried out separately using *any preferred oil drift model* that can provide the necessary parameters in the right format for input to ERA Acute. The format (the parameters and their units) is specified a separate report (Brönner et al. 2017).

A Defined Situation of Hazard and Accident (DSHA) may consist of one or several scenarios (see Sect. 3.1) where each scenario represents a rate-duration combination and a spill location depth and is modelled in numerous simulations. The scenarios have different probabilities, defined by a probability distribution. Single simulation results must contain the oil exposure-related input parameters for each compartment in each cell. Initial impacts are calculated in individual cells of single simulations for every VEC. The impact mechanisms are different in each compartment. Results from the cells and simulations are aggregated to scenario statistics and DSHA assessments using the probability distributions of the individual rates, durations and spill depth. In this way, results are averaged and/or summarized in a series of steps that allow the investigation of results at several levels. Impacts can be viewed in individual cells and for single simulations or can be summarized for scenarios or whole DSHAs. A case can consist of one or more DSHAs.

In order to include the large variation in drift and fate of the oil following an accidental oil spill, the oil spill modelling is carried out using a stochastic approach with numerous simulation runs using different historical start dates, representing a variety of wind and current situations throughout the simulated spill and modelling duration from a hindcast archive of historical wind and current. The output is a significantly large number of spill simulations, each representing a historical situation of how the oil spill would have behaved and impacted different areas on the sea surface, water column, seafloor or shoreline had it started on a specific historic date. In this way seasonal and annual variations are included in the statistical results. For each oil spill simulation, various endpoint parameters are recorded for each grid cell that will be used to quantify the impact (mortality or habitat loss) for various VECs. This includes parameters like:

- oil *mass* and oil *film thickness* on the sea surface
- surface oil *coverage* in grid cell above a threshold film thickness
- accumulated oil *mass* in shoreline or seafloor grid cells

- total water column *concentrations* of oil (droplets and dissolved oil components) or a potential *accumulated fish larvae mortality* calculated over the duration of the simulation based on the composition of the hydrocarbons at each time step and their toxicity, if available from an external model.

Many of the input parameters to ERA Acute from oil drift modelling are averaged over the spill simulation time steps, i.e. oil film thickness is the average oil film thickness in a grid cell when there has been oil in the grid cell during the simulation. For the shoreline and seafloor compartments, the accumulated oil mass at the end of the simulation is recorded and given as output of the oil drift model, in turn used as input to ERA Acute to quantify the impact in these compartments.

1.4.2 Valued Ecosystem Components

As mentioned, a VEC in ERA Acute is a natural resource for which the environmental risk is assessed. VEC data are used for the more detailed levels of analysis in ERA Acute (see description of the levels in Sect. 1.3.3) and VECs are assigned to an environmental compartment of their primary exposure. The VEC can be a population of seabirds, turtles or marine mammals, sensitive early life stages (ELS) of a fish population, a shoreline type or seafloor species or habitat/community "represented" by a key species.

1.4.2.1 Analysis Level A.1 Impact Analysis

At level A.1 impact analysis, VEC data are not needed (see Sect. 1.3.3.1).

1.4.2.2 Analysis Level A.2 Impact Analysis

If VEC data are limited to a geographic area comprising the location and extent of a habitat of a species, a spawning area or similar, but no details are known about the density distributions within that area, simplified VEC data can be prepared for a compartment to allow for an ERA Acute analysis at level A.2. The data are simple gridded polygon data where the VEC may be present (see Sect. 3.2.1), which will be matched with the oil spill input to limit the impact assessment to specific areas. Many globally available GIS data are readily available for this level, requiring only gridding of the polygons.

1.4.2.3 Analysis Level A.3 Impact Analysis

VEC input data at the highest level are gridded to the same standardized format as oil spill trajectory simulations, containing VEC population (or equivalent) fractions in each cell. Each VEC is ascribed to the compartment where the main impact occurs. The parameter values used for the VECs can be changed where relevant, e.g. for different regions, but globally applicable default values are available.

In order to calculate the most detailed potential impact and recovery of a VEC, its distribution needs to be mapped into the same grid cells as the oil drift output. For a population, each grid cell will have a value representing the fraction of the population present in that cell. Environmental risk will vary between seasons with the VEC distribution, the VEC distribution data therefore have a monthly resolution. For shorelines, the shoreline length of each ESI ranking (NOAA 2002) in each grid cell is used as the VEC unit. For seafloor habitats and/or communities, the area distribution in km^2 within each seafloor grid cell is used.

The VEC data are entered for each of the four environmental compartments in ERA Acute (Fig. 1.3):

- Sea surface compartment—(Sea birds, marine mammals, turtles)
- Water column compartment—(Fish stocks represented by eggs and larvae)
- Shoreline—(ESI shoreline ranking of shoreline)
- Seafloor—(Benthic habitats/communities or key species).

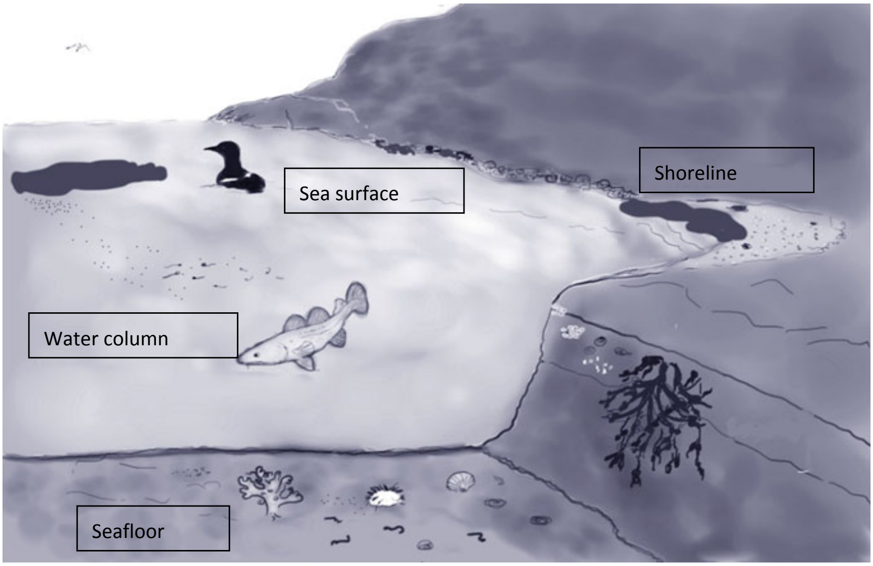

Fig. 1.3 Valued ecosystem components are natural resources that are assigned to one of four compartments sea surface, water column, shoreline or seafloor (Illustration C. Stephansen)

As for oil drift simulations, VEC-data are entered as input data to ERA Acute. Figure 1.4 shows a map of a monthly distribution of a sea bird VEC with partial data coverage.

The distribution of a VEC population within an area is sensitive to the quality of data, which directly affects the accuracy of the impact calculations. VEC data at the A.3 level should be prepared using caution and scientific approaches to handle uncertainty (see Chap. 4). Sources of quality data from specialist scientific institutions that carry out VEC distribution modelling, validated with observations are preferable. For example, for seabirds, colony data with additional foraging area distributions around the colonies are relevant for breeding seasons, whereas data for

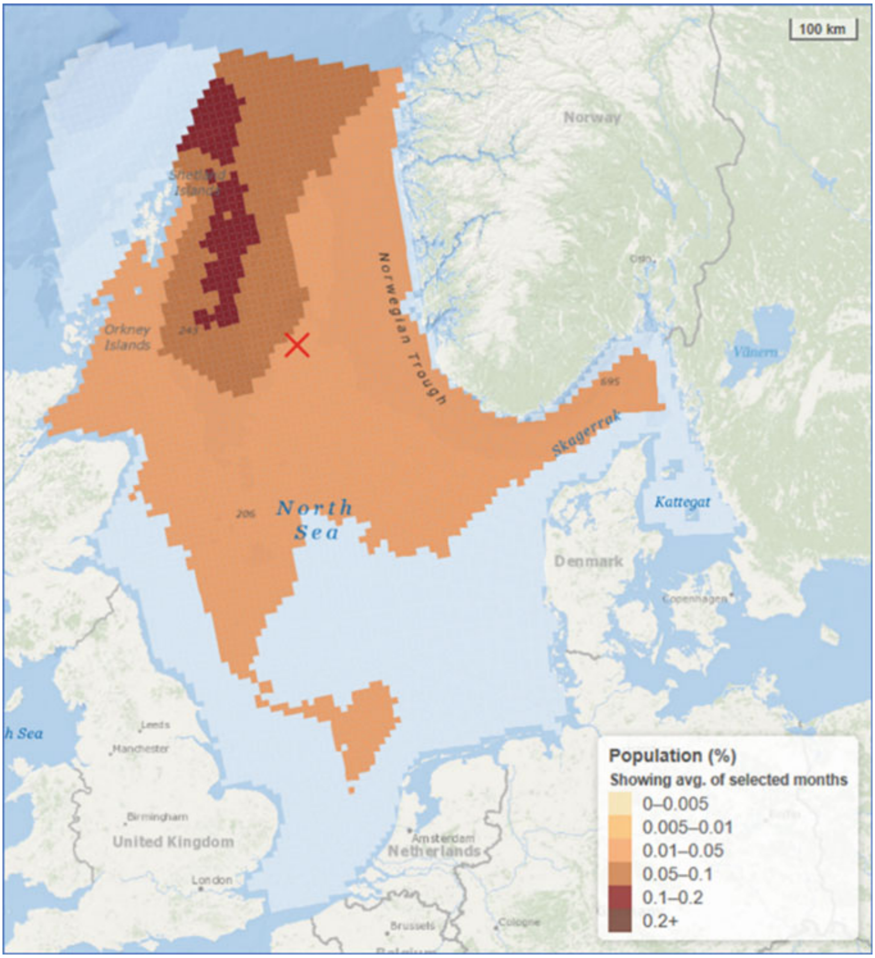

Fig. 1.4 Example of a monthly distribution map showing population fractions of a seabird VEC in each grid cell with a limited geographic coverage of the data set

migration and wintering areas could be established using loggers and other tracking devices, machine learning techniques etc. to estimate and validate distributions. For NCS, the authors have prepared industry standard seabird data using species distributions from the specialist scientific institutions Norwegian Polar Institute (NPI) and Norwegian Institute of Nature Research (NINA) under the SEAPOP and SEATRACK programs (http://www.seapop.no/en/). Data prepared by agent-based modelling under MARAMBS (Marine Animal Ranging Assessment Model Barents Sea, DHI) (http://marambs.dhigroup.com/) have also been utilized. Construction of VEC data for the international validation cases are described in Sect. 4.1.4. For all ERA Acute parameters, default values are suggested based on assessment of available scientific knowledge. However, parameter values related to the VEC and specific population in question should be assessed, tested and if necessary, adjusted and validated for the specific VEC population.

1.4.3 Model Input Parameters

ERA Acute calculation functions use many parameters which have values that are specific for certain species or regions (upper right light orange box in Fig. 1.1). Recommended values based on literature studies are supplied for use in the Northern Atlantic/NCS region with the software tool and documented in the methodology development reports (Bjørgesæter and Damsgaard Jensen 2015; Brude et al. 2015; Brönner et al. 2015; Stephansen et al. 2015). These values can be changed by the user if other values are considered more appropriate for another specific region or when future research provides new knowledge. However, it is strongly recommended to obtain consensus for the parameter values used in analyses that are carried out for example within the same regulatory framework or region, in order to compare analyses.

1.5 From Spill Scenario to Case and from Damage to Risk

The basic concepts of impact and recovery calculation in ERA Acute have been described in Sect. 1.3 and are described in greater detail in Chap. 3. In order to calculate risk from the estimated consequences, the probability of the damage also has to be taken into account. For this, the case needs to be analyzed with the correct distribution of probabilities between the elements that contribute to the risk.

To give an example, say a risk assessor needs to analyze the annual environmental risk related to accidental oil spills for an oil field in production. This is the *Case*. The possible spills that contribute to the analysis case may be different DSHAs (see Sect. 1.4.1) A DSHA may be pipeline leakages or blowouts from loss of well control during drilling or maintenance, or other spill scenarios related to the activity or annual activities on the field. The first step is to define which DSHAs that make up the case

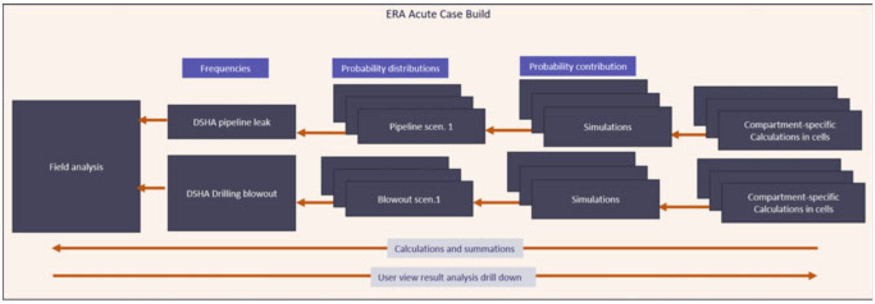

Fig. 1.5 A case can consist of several DSHAs that in turn consist of one or several scenarios. For each scenario several simulations are run (with equal probability contribution within the scenario), giving results in cells

to be analyzed, and to determine the frequency for each. Each of these DSHAs have individual frequencies (probabilities of occurring) per annum or per activity, based on statistics from historic incidents.

A DSHA in turn consists of one or several spill *scenarios*, which in ERA Acute is defined as a spill situation characterized by all the properties of the scenario where the rate and duration differ between the scenarios. One scenario within a DSHA is defined by a spill rate and duration combination, all other properties (location, oil type etc.) are the same within the DSHA. A blowout DSHA, for example, may consist of many spill scenarios representing surface or seabed releases or a range of blowout rates and durations representing spills from open hole, annulus or drill pipe. The spill scenarios are commonly presented in a rate-duration matrix with a probability distribution between the scenarios, given as input to the calculations.

For each scenario, several oil drift simulations are run as described above. The calculations are run “bottom-up” starting with the single cell calculations in the simulation and ending with the results for the whole case.

The results are typically viewed from the case perspective and drilled down to scenarios for example to illustrate which of the spill scenarios contributes the most to environmental risk (Fig. 1.5). As oil and gas activities can have many different spill scenarios, it is also relevant to show the individual risk for each spill scenario or the aggregated risk of the DSHA or the Case. From a scenario, results can be drilled down even to single simulations, relevant e.g. for viewing extreme situations. Figure 1.6 shows this model framework up to a DSHA.

1.6 What Can ERA Acute Results Be Used for?

ERA Acute has many endpoints (impact, recovery times and RDF), and the flexibility in the use of data detailing makes ERA Acute useful for both screenings and more in-depth risk assessments in several Environmental Risk Management applications (see Chap. 2).

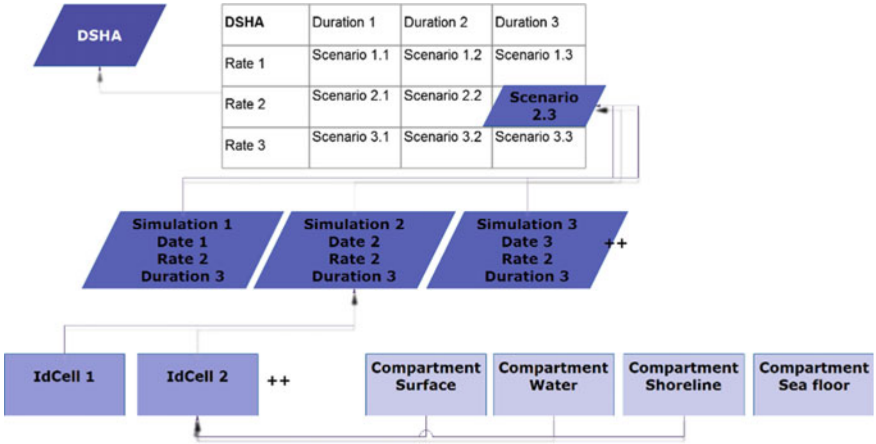

Fig. 1.6 Structure of ERA Acute with four compartments and cell and simulation-to-DSHA build. Each of the spill scenarios has a probability

Results are presented as average impacts or time factors, maximums and minimums, as graphs of monthly results for one or several VECs, probability distributions and frequencies. A common set of recommended presentation formats are developed to facilitate standardized analyses and user-friendly risk analysis endpoints. In-depth knowledge of the sensitivities of the model and its inputs is a necessary background for setting operator-specific boundaries of risk acceptance for each endpoint, as well as adapting datasets and input parameters in the model.

As mentioned, at its most detailed level, ERA Acute requires several types of input data as well as understanding of the implications of the analysis area scale and the transparency of input data. Screenings from the first levels provide a good basis for decision-support in early stages of project development, whereas the most detailed results are beneficial in other environmental risk management processes, authority applications etc. Endpoints from a variety of calculation steps can be presented or post-processed to answer questions in analyses such as ERAs or impact assessments or can be used to compare and select the response option(s) that will best mitigate the overall impact and risks such as for Spill Impact Mitigation Assessments, Net Environmental Benefit Analysis and company-specific risk matrix approaches (see Chap. 2). It can therefore provide quantitative input to comprehensive comparative methods such as described by Bock et al. (2018), which may also include stakeholder engagement processes and value-based weighting/scoring.

The use of a continuous function in the impact calculations is expected to be valuable when comparing e.g. risk mitigation by use of oil spill recovery options, since the impact calculations will be able to better detect the effect of small variations in exposure than a model based on oil amounts in categories. Category-based models will assume the same impact probability distribution whether the oil amount is the lowest or the highest amount within the category interval. For example, in MIRA the impact is the same whether the oil amount in a cell is 1 ton or 99 tons, whereas 100 tons of oil brings the impact into the next impact category. Using the continuous function in ERA Acute will mitigate this shortcoming and is especially useful for comparing risk between alternative cases and solutions, such as for SIMAs. Although in some cases a category-based method may result in higher impact for a small spill, a continuous function will be more sensitive to subtle changes in exposure. ERA Acute is therefore expected to be more suitable for analyzing efficiency of mitigation of smaller spills than a category-based method, which is especially important in environmentally sensitive areas.

Because ERA Acute quantitatively evaluates the impact and risk in grid cells, risk assessors can view results in maps at various assessment steps using a geographical information system for any region globally. An ERA Acute environmental risk map for a VEC can show where the risk is high or low, for example by showing average population loss from all simulations or by highlighting the worst case by showing maximum population loss. The environmental risk assessor can identify areas of high risk for use in decision support and spill response planning, independently of the region. All georeferenced results are useful for strategic use of geographic information in risk management and planning.

For detailed studies of scenario impacts, analysis endpoints can be plotted against frequencies in *risk matrixes*. Since many spill simulations have been carried out for each spill scenario, a probability distribution is obtained of different outcomes in terms of environmental damage. The various impact and recovery time endpoints in ERA Acute can be categorized according to level of seriousness and the probability for defined categories of environmental damage can be calculated, e.g. "minor", "moderate", "serious" etc. These severity categories are subjective, based on operator preferences or industry standards where relevant (see Chap. 2 for more detail). The applications of the methodology are discussed in Chap. 2.

1.7 Model Sensitivity and Uncertainty Issues

As a quantitative impact and restoration model, The ERA Acute methodology attempts to describe in mathematical terms the magnitude and duration of the impact from an accidental oil spill. The ability of such a model to accurately quantify the relationship between the exposure and the impact in terms of mortality depends on our understanding of underlying mechanisms of harmful action and how well these can be implemented into mathematical functions. In developing such models, there are numerous decisions to be made, regarding e.g. complexity versus data availability, simplification versus inaccuracy etc. It has been a major goal of the project to develop a model that could be used robustly if there is a low availability of data on presence of resources, but also to be able to utilize high-quality data where these are available.

As a model that uses data on resource presence and exposure-parameters from oil drift simulations to determine exposure and lethality probabilities (denoted p_{exp} and p_{let}, described in Chap. 3), the model is naturally sensitive to these and other inputs.

Transparency is therefore needed when presenting results, and as with all other models, users need to verify both data coverage and applicability before entering data into the model. It is recommended that VEC data from the different levels (A.1, A.2 and A.3) are not mixed in the same analysis, e.g. by using presence/no presence data for one VEC and fraction of populations for another VEC, as the calculated results reflect the VEC cell value directly. Different data types should be separated when showing results. Many options are possible for the VEC "unit", the parameter that defines the seasonal and geographical distribution (denoted N in calculations), and the ERA Acute industry guideline (NOROG 2020) will advise on data use for standardized applications of the ERA Acute methodology, including setting the analysis scale. The model implementation software handles differences in data set *levels* but uses the VEC distribution parameter-value transparently and directly. Users must therefore still apply scientific caution when using data sets from different sources, especially when comparing and interpreting results, as is the case for all models.

Comparing results between compartments can be particularly challenging in models like ERA Acute, because the impact calculations are based on compartment-specific modes of action and ERA Acute therefore uses compartment-specific functions behind the calculations of lethality and exposure. In e.g. the surface compartment, laboratory-controlled experiments cannot be used to determine the quantitative relationship between dose and response. For some mechanisms, such as smothering or oiling on feathers, a dose-response relationship may not even be clear, although we intuitively understand that a large spill may have a higher impact than a smaller spill. Different approaches have therefore been used in the model development, utilizing as far as possible the knowledge available of impact mechanisms, impact magnitudes after known oil spills and various theoretical approaches. Since the units of the VEC distribution parameter-values and therefore also the endpoints are different, the numerical results in compartments cannot be compared *directly*, but users may compare for example results as relative to a maximum or in severity categories carefully defined for each compartment. Relative differences in risks within a single compartment may be compared directly between cases. Comparisons are relevant e.g. in SIMA analyses. Keeping the integrity of each compartment is important, both when it comes to the possibility for the analyst to interpret results clearly and for the use of the different endpoints in practical applications. Weighting the result-levels between the four compartments has so far not been part of the methodology development. Also, under different regulatory frameworks there may be different requirements regarding weighting between VECs and/or compartments, or to which degree stakeholders are involved in the assessment process or whether the management process includes stakeholder value scoring of VECs (e.g. Bock et al. 2018).

ERA Acute uses a series of input parameters that are entered into the model at various stages. The ERA Acute methodology has been tested with respect to sensitivity towards important input parameters, using statistical and deterministic testing methods as part of the uncertainty handling (Chap. 4). The model is flexible in design by allowing the user to change some of these parameters if other values are more relevant regionally. However, *within* a region, it is recommended that the parameters are used with consensus within the industry, to obtain comparable results between analyses. As an example; for sediment substrates, finding as accurate as possible values of e.g. total organic carbon content (TOC) will improve the result accuracy. On the other hand, measurements of TOC vary greatly with the local conditions (e.g. background contamination) and the uncertainty may be high. The sensitivity of each model step to its parameters was therefore the subject of a separate study in the project and is the focus of Chap. 4. The input parameters and the proposed standard values were tested for their relative importance to the outcome of the model in the sensitivity and validation phase of the project.

As far as possible, results have also been validated against impact estimates from two historically important oil spills, the Exxon Valdez Oil Spill and the Deepwater Horizon Oil Spill. Comparing the model against historic spills is a particularly interesting and challenging task described in Chap. 4 “Testing and Validating against Historic Spills”. Whilst such model validations have many limitations, as impact assessments from the historic spills in themselves also contain uncertainties as results of modelling and calculations, we found that the results of ERA Acute calculations fell within the boundaries of the impact estimates from the spills. We therefore believe that the model is ready to be used and that further experience and work will refine and improve it over time.

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Chapter 2
Environmental Risk Management Applications of ERA Acute

Abstract ERA Acute supports a variety of analyses, from simple screening studies based on oil spill statistics and potential impact areas to more in-depth impact and recovery calculations on species and habitats. The ERA Acute software tool has been built to enable and provide ease of use of the methodology and results. Visualizations of impact and risk areas can be made at several levels, from simulations and scenarios to whole cases. Results can have a monthly resolution to show variations throughout the year. This enables a wide range of decision-support from risk screening studies, impact assessments, risk quantification, risk management including effect of mitigating measures (NEBA/SIMA) evaluations to properly inform oil spill response planning. The methodology is suitable for global use and will be the recommended approach for oil spill risk assessments for offshore operators on the NCS.

Keywords Environmental risk management · Net Environmental Benefit Analysis · Spill Impact Mitigation Analysis · Environmental risk assessment · Environmental risk screening

2.1 Introduction

Environmental risk management in activities representing a possibility for oil spills is directly linked to ERA, since the ERM process utilizes the results and insights produced by an ERA (Venesjärvi 2016).

Quantitative ERAs are used to support decision makers in complying with regulations, e.g. for activity applications, planning processes and as input to oil spill response planning. This chapter provides an overview of risk management application areas with the newly developed ERA Acute methodology for acute oil spills (Libre et al. 2018; Stephansen et al. 2017a, b). Various endpoints and high degree of flexibility ensure many usage areas for ERA Acute. Environmental risk screenings may provide sufficient decision support in early stages of project development or concept selection and can be a viable endpoint in areas with restricted access to input data, whereas the most detailed assessment and results are found to be beneficial in several environmental risk management uses, e.g. ERA, impact assessment,

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NEBA/SIMA or as input to company-specific risk matrix rankings. In many areas the VEC data may be limited or less detailed, in which case ERA Acute provides a possibility to carry out more conservative calculations.

Impact and risk illustrations used herein are for illustration only and are made with the ERA Acute software.

2.2 ERA Acute Usage Areas

ERA Acute is an enhanced and globally applicable quantitative oil spill risk assessment methodology (meeting the guidelines set by IPIECA-IOGP 2013) and software tool, and is applicable for various risk assessment purposes, depending on user's need and data availability:

1. Risk screening
2. Input to concept selection/risk comparison
3. Environmental impact assessments
4. Site-specific decision making
5. Risk estimation and evaluation/risk ranking

Evaluation and prioritization or risk reducing measures; e.g. ERA Acute can provide quantitative input to NEBA/SIMA in order to inform oil spill response planning (IPIECA-API-IOGP 2017). Questions that can be answered using ERA Acute are:

- What is the possible impacted area of a spill scenario?
- What are the possible consequences to species and habitats in the various environmental compartments?
- Could there be a risk for adverse environmental effects?
- What is the probability for different consequences, i.e. what is the risk?
- Where will the highest impact be?
- In which areas to we need to prioritize oil spill response?
- How much do different mitigating measures reduce the impact or risk?

2.3 Environmental Risk Screening

The screening is the first phase in an ecological risk assessment, i.e. to decide on the distribution of stressors in the environment and the extent of contact where exposure could occur (US EPA 1998). ERA Acute is based on oil spill modelling of specific oil spill scenarios which make up a DSHA (see Sect. 1.5). Oil spill modelling enables researchers and others to estimate potential impact and utilize the results in ERAs, including cost-benefit and decision analyses (French McCay et al. 2004). This leads to informed decisions in strategic planning and/or operational management (Jakeman et al. 2006).

The output from stochastic oil drift modelling provides a statistical overview of oil spill trajectories and to what extent certain areas could be exposed to harmful oil. Without saying anything about the presence of sensitive resources or habitats, and just by analyzing the results from a high number of different oil spill trajectories, the screening process can highlight areas and periods of environmental concern in different environmental compartments. This is denoted level A.1 (see Sect. 1.3.3.1).

The ERA Acute software tool can visualize important features from the oil spill modelling such as probabilities of oiling above an effect threshold value (i.e. surface oil film thickness or water column concentration), and statistical parameters such as minimum, mean and maximum values of oil volumes and concentrations in geographic areas. All oil spill parameters can be visualized in a map in an ERA Acute screening assessment. The risk screening can as such define the boundaries for further detailed impact and risk assessments, provide insight into the needs for further data gathering or inform concept selection in an early stage without extensive assessment approaches.

Assuming that certain species with specific oil spill sensitivities are present within the spilled area (Level A.1), the ERA Acute screening can also estimate the expected mortality of such a species in this area (Fig. 2.1, left). By adding information on the spatial-temporal distribution of the VEC in an area in the form of a data set of presence/non-presence, the first screening of probable impacts and impact areas can be further refined and examined (level A.2). The area of average potential mortality may for example be narrowed down to a particular seabird species/population in the breeding season within the breeding area (Fig. 2.1, right) (see Sect. 1.3.3.1).

In addition to the statistical results, visualization of single simulations is a possibility within the ERA Acute software tool. This is applicable for illustrating e.g. a

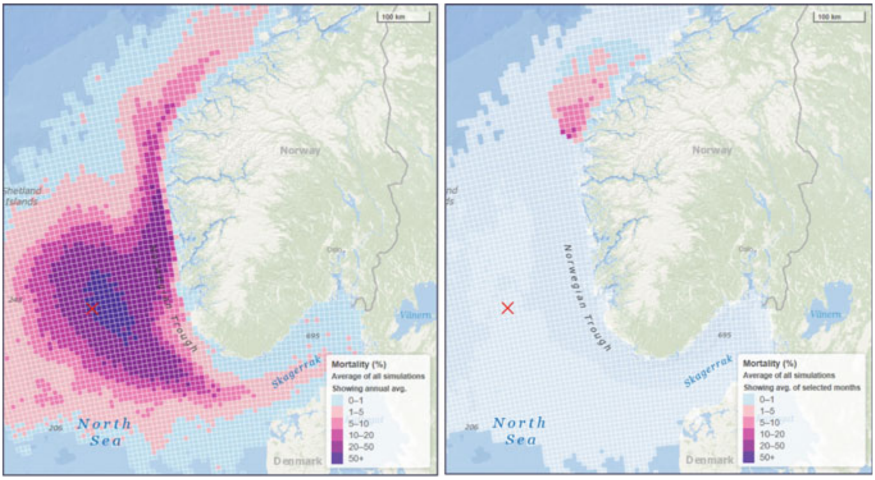

Fig. 2.1 Probable seabird impact (% mortality) in 10 × 10 km grid cells from stochastic oil spill simulations (left) and restricted to the breeding area of northern gannet in the breeding period (right)

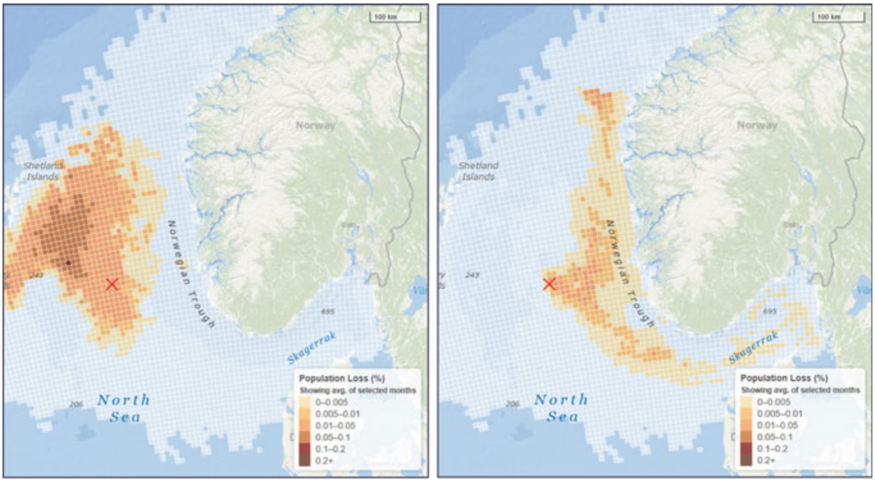

Fig. 2.2 Example of calculated mortality for a seabird from the simulation with the maximum (left) and minimum (right) impact potential on the sea surface from stochastic oil spill modelling in a North Sea scenario

percentile worst-case simulation in terms of shoreline volumes or drift time to shore, or a selected simulation with impact in certain areas of interest (Fig. 2.2).

2.4 Damage and Risk Assessment

A complete damage assessment in ERA Acute is based on quantification of impact (e.g. population/habitat loss) and the duration of the impact until recovery (pre-spill conditions). The Resource Damage Factor (RDF) is calculated as the integral of the extent of impact and duration of impact until recovery. For damage assessments, the probability for different outcomes is calculated and can inform on the likely damage which is typically the case for environmental impact assessments.

The level of available or applicable temporal resolution of VEC data sets the frames for output resolution. For VEC data available as monthly distributions (e.g. seabirds, marine mammals), the impact and risk calculations can present impact levels and species at risk on a monthly basis. The example in Fig. 2.3 shows the monthly average population loss from a blowout scenario on 5 different seabird species. The results show high impact on northern gannet in the winter period from November to March and for northern fulmar in the autumn from August to October. Results as presented, will be of high value for risk management, e.g. if these were results from an analysis for an exploration drilling activity, they show that for these populations of seabirds, the potential impact is relatively low in the summer months. These results could be used further in an “ALARP assessment”, where e.g. the drilling period could be one element to assess.

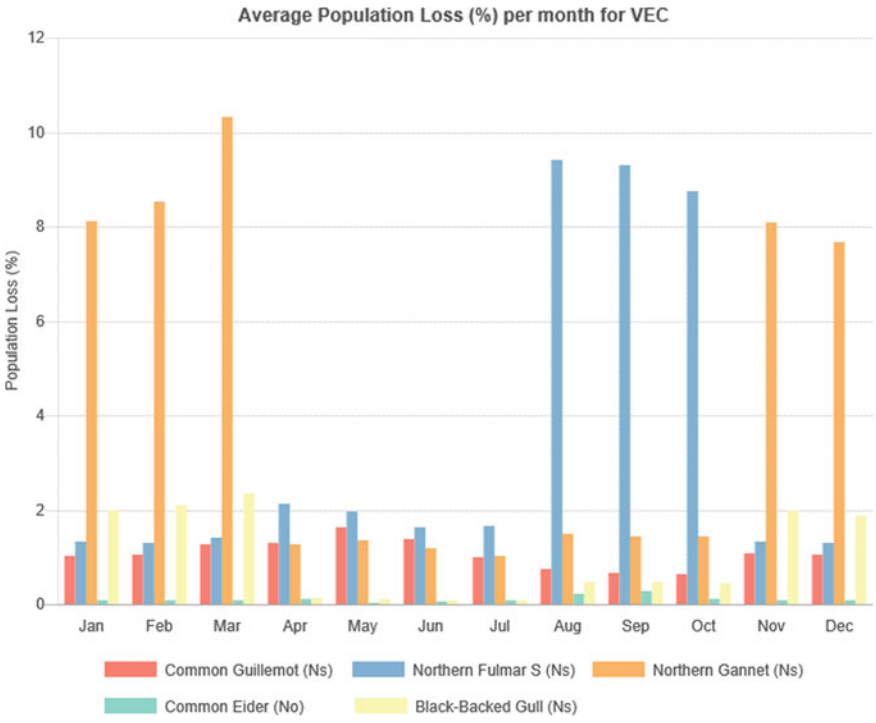

Fig. 2.3 Example on calculated monthly average population loss for 5 seabird species from a blowout spill scenario

As there is huge variation in spill trajectory and fate of the oil due to variations in wind and currents, as well as in the distribution of VECs, the different outcomes from each spill simulation can be categorized according to severity and then presented as probabilities for different impact/damage categories (Table 2.1). Such approaches are viewed beneficially for oil spill risk assessments where the extent of oil-induced damage may vary greatly (Hilborn 1996; Lecklin et al. 2011). The consequence probabilities can be presented as frequencies if multiplied with spill scenario frequency in line with ISO 17776:2016.

Table 2.1 Probability for different impact (population loss) categories for Atlantic puffin in the breeding season (May to August) based on stochastic oil drift simulations for a given spill scenario. Examples of categorization. The number of categories can vary

Population loss (%)	Category	Probability (%)	Frequency
<5	Minor	77.78	8.17E−5
5.0–10.0	Moderate	8.33	8.75E−6
10.0–20.0	Serious	4.41	4.63E−6
>20.0	Very serious	9.48	9.95E−6

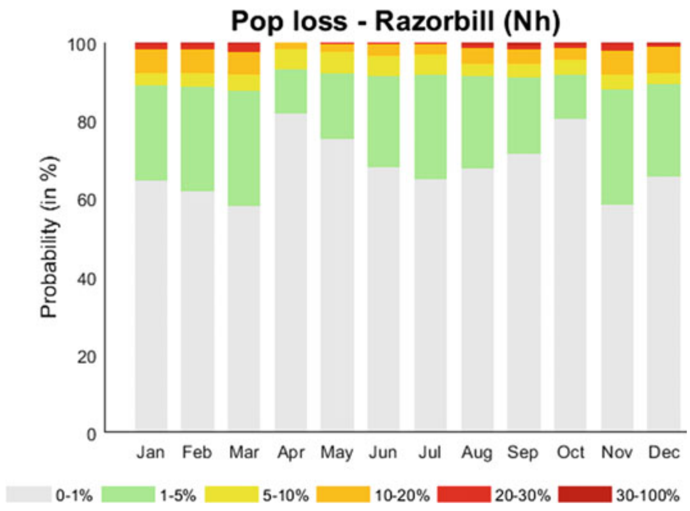

Fig. 2.4 Calculated monthly probabilities for various population losses (%) for razorbill for a spill scenario (with hundreds of spill simulations in each month)

Several endpoints can be used to categorize or classify the environmental damage in various seasons or months. This includes population loss on a species level for sea surface and water column species, impacted shoreline (in km) or seafloor (in km^2), recovery time (in years) or RDF (in population loss years or habitat impact years), see example in Fig. 2.4. Endpoints can be used separately or in combinations to categorize a damage, e.g. to calculate the combined probability for a shoreline impact above 50 km with habitat recovery time above 10 years.

In stochastic oil spill trajectory modelling, several oil spill scenarios can contribute to the overall risk for the planned activity. To identify the scenario(s) that contribute most to risk, ERA Acute can be used to compare the various impact and risk endpoints for each spill scenario separately in addition to a DSHA summary. This is illustrated in Fig. 2.5 where the calculated probability for different population losses for a seabird species is presented and compared for each spill scenario (each combination of spill rate and duration) in a topside blowout, this in order to inform about which scenarios that could have a substantial or possibly irreversible effect on the population. In the given example (Fig. 2.6), only blowouts with 60-days duration will have the possibility for population losses exceeding 30%, while the 2-day duration blowout scenario most probably would have a population loss below 1% even for a spill rate as high as 9000 m^3/d.

The example in Fig. 2.5 shows an outline of the drill down possibilities in the ERA Acute results. The impact from specific oil spill simulations (specific start dates) can also be selected and visualized in order to investigate specific situations and to further inform oil spill response planning and operations. Figure 2.6 (left) gives an example of the calculated impact (population loss) for northern gannet in the breeding season from a blowout spill scenario with a ranking of simulation results from highest to

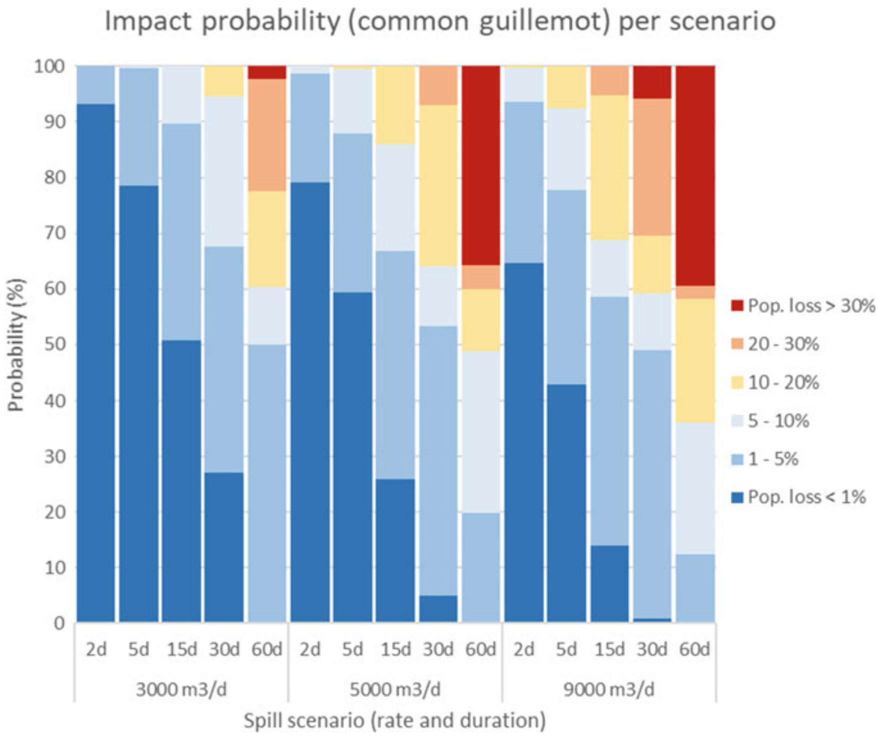

Fig. 2.5 Probability for various population losses for Common guillemot calculated for 15 different topside blowout scenarios (combinations of spill rate and duration)

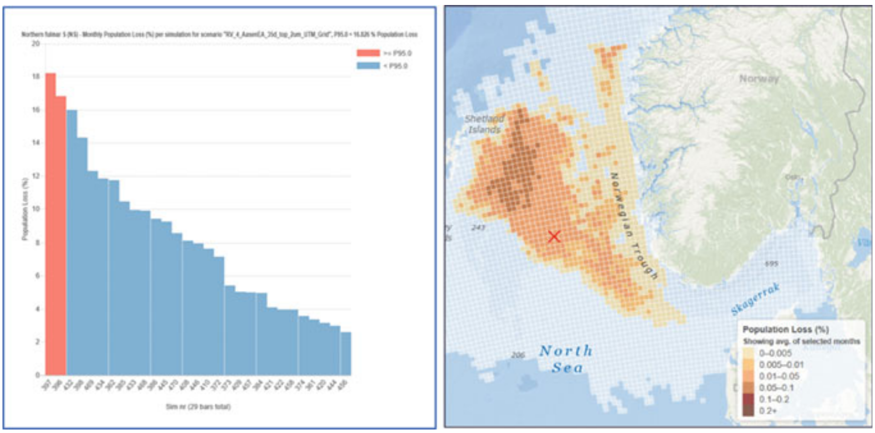

Fig. 2.6 Ranking of calculated population loss of northern gannet from highest impacting simulations (left figure). Shift between red and blue in the left figure indicates the 95-percentile level and the impact from this simulation is illustrated with calculated population loss per 10 × 10 km grid cell (right figure)

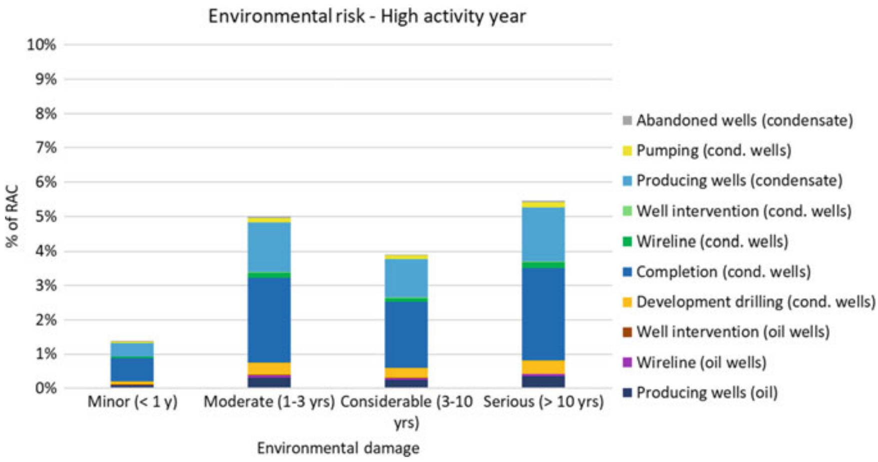

Fig. 2.7 Environmental risk overview for various activities from a producing oil field in a high activity year with several well operations and development drillings. Here, an example measured against the operator's own Risk Tolerance Criteria (RTC) and categorization

lowest impact (left to right), and a map showing the impact in grid cells from the 95-percentile worst-case simulation (Fig. 2.6, right).

An oil-producing installation case can have several DSHAs (i.e. a blowout, a process leakage, a pipeline spill etc.) and each DSHA can consist of several spill scenarios (i.e. a blowout can have different spill rates and durations with different probabilities). Therefore, the risk results can be aggregated on the DSHA and case level, with possibilities to look at specific contributions and details from the underlying spill scenarios (Fig. 2.7). This will give valuable information towards the understanding of risk-contributing activities and towards the planning of field activities.

Once the risk has been established, the primary objective is to evaluate the risk level and to communicate activity or scenario risk to stakeholders and decision-makers in a logical and understandable way. ERAs are carried out with the purpose to assess and ensure acceptable environmental risk for oil and gas offshore operations. To ensure this, the risk level can be evaluated against risk tolerance criteria (RTC), and/or properly informed decisions (e.g. using the ALARP principle) can be made regarding the implementation of risk reducing measures to achieve a tolerable risk level (IPIECA-IOGP 2013).

ERA Acute provides the necessary input to a traditional risk matrix by giving the probabilities for different operator-defined damage categories (Fig. 2.8). In the risk matrix, risk tolerance criteria define the threshold for a tolerable likelihood of an environmental damage (EPA 2007; NORSOK Z-013 2001). Alternatively, risk can be presented as a percentage of a certain RTC for different species or habitats, where values above 100% represent risk level exceeding the RTC (NOROG 2007).

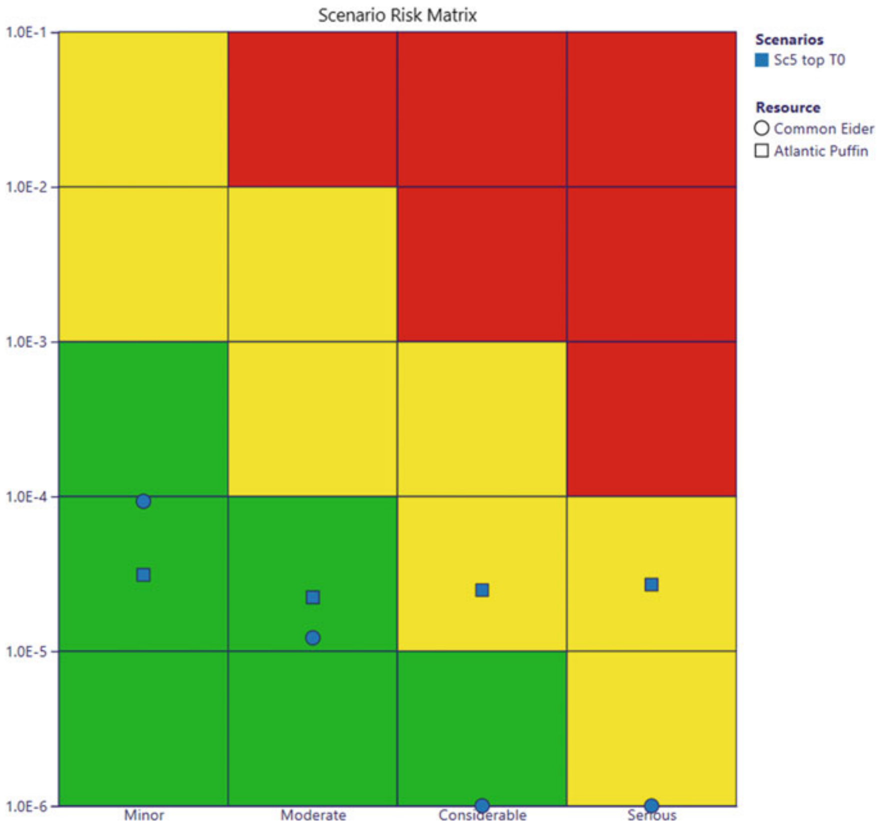

Fig. 2.8 Example of risk results for two seabird species from a spill scenario plotted in a risk matrix where the size of damage (x-axis) is categorized from RDF values and spill frequency (y-axis). Risk tolerance criteria has been set to the different damage categories and frequencies (red = intolerable risk; yellow = ALARP level; green = acceptable risk)

2.5 Risk Mitigation and Net Environmental Benefit Assessments

Identification of possible risk reducing measures is typically performed as a part of the risk assessment process (Wenning et al. 2018; Bock et al. 2018). The quantitative ERA Acute approach is suited for evaluating and visualizing probability and consequence reducing measures to reduce risk, e.g. recalculation of risk when a risk reducing measure changes the spill scenarios. The probability of a scenario can be reduced, or the oil spill response may change the actual spill scenario's fate and trajectory. As such, the method can be used for quantitative input to NEBA/SIMA (IPIECA-API-IOGP 2017). Revised oil spill scenarios or probability distributions can be entered in the model and the re-calculated environmental risk levels can be easily compared to the original output, to evaluate the effect of the mitigating measures (see example

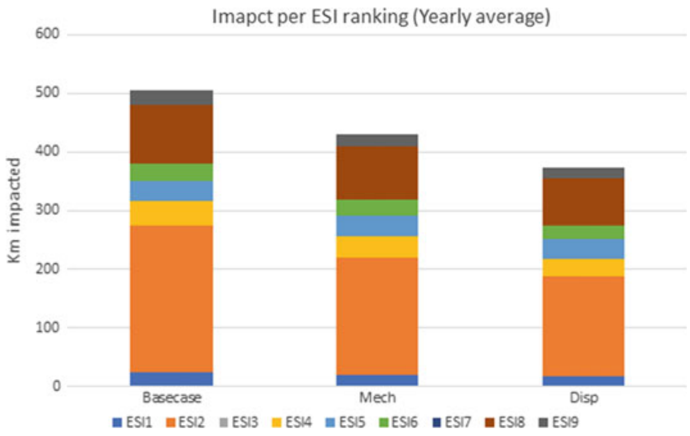

Fig. 2.9 Comparison of shoreline impact (km) from a blowout scenario with and without spill response options. Basecase = no response; Mech = surface mechanical response; Disp = surface chemical dispersion

in Fig. 2.9). The foundation principle that ERA Acute uses continuous impact and damage algorithms, means it is well-suited to reflect even minor changes in spill scenarios or resources distribution as a change in impact and risk.

In the ERA Acute software tool, a separate comparison module enables the user to compare oil spill trajectory, impact and risk data from different scenarios or calculations in a straightforward manner. This can be performed as compartment or resource impact and risk summaries but also plotted as impact maps. This is important in balancing the trade-offs by weighing and comparing the range of benefits and drawbacks associated with each response option (IPIECA-API-IOGP 2017).

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Chapter 3
An ERA Acute Model Overview

Abstract ERA Acute is a model for environmental risk assessment of acute discharges. The calculations follow a common framework for all environmental compartments, whilst maintaining the mechanistic integrity of each compartment and/or VEC group, by using compartment-specific inputs of oil exposure and VEC-specific geographical distribution, vulnerability and recovery-defining parameters/functions. The method allows for using three different levels of detailing in VEC in the exposure and impact calculations. For the highest level of detail, a second step calculates recovery times in three time-factors, as well as the ERA Acute-specific RDF which combines the extent of impact and recovery. The continuous functions of impact and recovery calculations are presented in this chapter, separately for all four compartments. All data are calculated in grid cells, facilitating the use of GIS for viewing inputs and results. The methodology adds up impacts from grid cells to populations, and calculates result statistics from single simulations to scenarios, to multi-scenario DSHAs and cases.

Keywords Environmental risk assessment · Oil spill risk assessment · ERA Acute risk functions · ERA Acute impact · ERA Acute restoration · Resource Damage Factor

3.1 Setting up the Case and Input to Exposure Calculations

Cases and DSHAs that are analyzed in ERA Acute can consist of one or several spill scenarios, each with a different spill rate, duration, depth (location), and probability distributions, set up in a rate-duration matrix. A DSHA can occur with a frequency, usually determined by historic spill statistics. Each oil spill scenario is modelled with multiple stochastic simulations, covering different simulation periods (start dates) and therefore representing different results of possible distribution of oil. The conceptual build-up of an analysis-case is described in Chap. 1, see also Figs. 1.5 and 1.6.

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https://doi.org/10.1007/978-3-030-70176-5_3

A rate-duration matrix including the probability distribution between rate (groups) and duration intervals can have different forms and detail, depending on the input given. A fictive, simplified example from a multi-scenario blowout-DSHA is presented in Table 3.1 and the frequency distribution is illustrated in Fig. 3.1. As a simplified alternative to the multi-scenario assessment, the DSHA could alternatively be a single scenario oil spill modelling restricted to one (weighted) oil spill rate and duration (100% rate probability). The DSHA frequency of a blowout from the example exploration drilling is 1.2×10^{-4}.

Each combination of rate and duration is run as a set of many simulations in oil spill trajectory modelling, given as inputs to ERA Acute for calculating exposure. The oil spill model results file must list results of each single simulation in the scenario, and must contain the following information for each grid cell:

- Sea surface: Oil film thickness, oil coverage and duration of exposure.
- Shoreline: stranded oil amounts.
- Water column: Concentration of total hydrocarbon content (THC_{max}) in the water column or potential mortality % if available from the oil drift model (see 3.6.1).
- Seafloor: Oil amounts on the seafloor.

Oil spill trajectory data are exported to the same grid as used for the VEC data and the connection between the two data types is the cell ID. VEC data and the additional input data needed for the exposure calculations are described for each compartment in the sections below.

3.2 Impact and Restoration Modelling

Calculations of damage are carried out in two main steps comprised of several substeps (Fig. 3.2). Step (A) calculates the magnitude/extent of the impact and Step B calculates the duration of the impact. Three time-factors are calculated from impact to recovery of the impacted VEC (see Fig. 3.2). The basic framework of the calculations is common between the compartments, including many of the general summaries of risks across cells, simulations and scenarios. However, compartments and/or VECs can be impacted and restored through different mechanisms of action and regrowth, as described in the compartment development reports (Bjørgesæter and Damsgaard Jensen 2015; Brude et al. 2015; Brönner and Nordtug 2015; Brönner et al. 2015, 2017; Stephansen et al. 2015, 2017a, b). Calculations of lethality and recovery time factors are therefore different between compartments. The common framework is described in this section.

3.2.1 Step A: Impact Modelling

All compartments build on the same general methodology framework for the basic impact calculation for a cell and simulation at step A; incorporating probability of

Table 3.1 Example of a rate-duration matrix where each combination of rate and duration makes up a scenario

Release point	Probability release point	Spill rate (Sm^3/day)	Rate probability	Duration (days) and probability distribution					
				2	5	15	35	55	70
Surface	0.1	1500	0.6	0.5	0.2	0.15	0.05	0.08	0.02
		3000	0.35						
		8000	0.05						
Seabed	0.9	1000	0.6	0.4	0.2	0.18	0.07	0.12	0.03
		4000	0.35						
		7000	0.05						

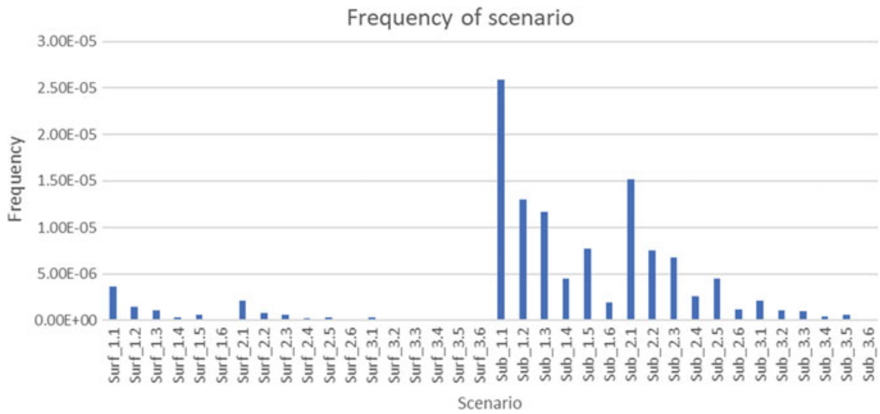

Fig. 3.1 Frequencies of each scenario from Table 3.1, where Surf = Surface spills, first digit represents the rate and second digit represents the duration. The sum of the frequency contributions is the DSHA frequency, 1.2×10^{-4}

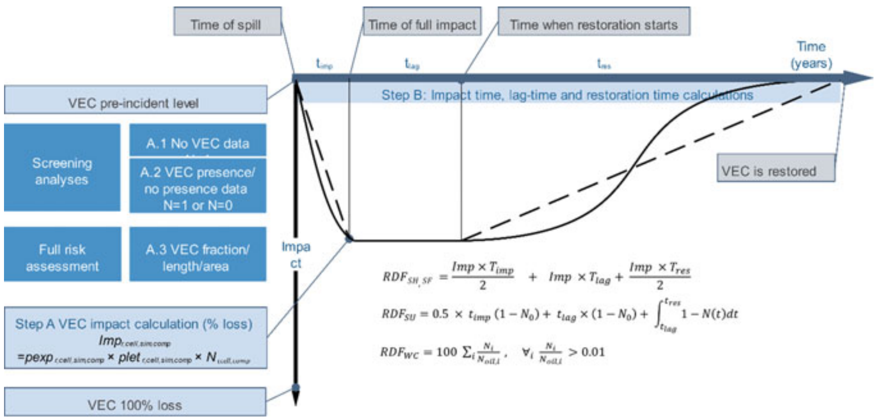

Fig. 3.2 Illustration of the impact (population/community loss) and restoration modelling in ERA Acute following a spill. Impact-, lag- and restoration times are defined along the time axis. The curve illustrates the initial steep decline in impacted resource, the increase in impact slows down until full impact is reached. Impact magnitude is at its maximum until restoration can start, which is illustrated by a re-growth curve. The area formed by the curve and timeline is the total combined expression of the impact extent and duration (surface) and water column compartments and simplified (dashed lines) for shoreline and seafloor

exposure, probability of lethal effect given exposure and abundance of vulnerable resources (Eq. 3.1) (Spikkerud et al. 2006 (Background Report 1)).

$$\mathrm{Imp}_{sim,cell,comp,VEC,month} = \mathrm{pexp}_{sim,cell,comp,VEC} \times \mathrm{plet}_{sim,cell,comp,VEC} \times N_{VEC,cell,comp,month} \tag{3.1}$$

where:

- *pexp*: Probability that the exposure will occur
- *plet*: Probability of lethal effect at the given exposure
- *N*: VEC unit in the grid cell. Population fraction (for sea surface and water column) km coastline (for shoreline types) or km^2 (for seafloor habitats).
- The calculation is carried out for each *Sim* (simulation), *cell*, *comp* (compartment) and for each *VEC*.

For each compartment and resource, the impact *Imp* is calculated for each grid cell in each simulation. For the month(s) that are covered by the oil spill simulation, results are reported in the cells with exposure to the VEC that has abundance above zero in the cell in the given month.

Although the impact calculations follow the same basic framework of Eq. 3.1, the functions used for calculating the factors *pexp* and *plet* values are different in the four compartments, reflecting that exposure routes and mechanisms of lethal action are different in the four compartments as well as between different resources and/or resource groups. Each compartment uses different relevant oil drift simulation input parameters in the exposure calculations.

As stated in the basic principles in Chap. 1, ERA Acute provides the opportunity to use different levels of detailing based on availability of resource data (see Figs. 3.2 and 3.3).

- Level A.1: If VEC data are omitted, ERA Acute assumes that sensitive resources are present in all cells in the analysis area ($N = 1$, ref Eq. 3.1), thus impact is dependent on exposure and lethality calculations for each cell.
- Level A.2: If the data sets are available in polygons with data on presence or no presence of biological resource data ($N = 1$ or $N = 0$, ref Eq. 3.1). Compared to A1, A2 will calculate impact only in cells where resources are present, eliminating cells with no presence.
- Level A.3: Fraction of VEC population present in the cell, adding up to $N = 1$ (100%) over all cells for sea surface and water column, length of coastal VEC type for shoreline or area of seafloor habitat. This level will provide an impact assessment of the total fraction of the population lost or total shoreline or seafloor impact. The data adaption (N-value) will directly affect the numerical value of the result and comparisons between compartments must be used with caution.

3.2.2 Step B: Impact Duration Modelling

The duration of the impact is calculated in step B, where the following time factors are defined:

- Impact time (t_{imp}), the time from the spill until full impact is seen (usually set to 1 year for a full annual cycle)
- Lag-time (t_{lag}), the time from full impact until recovery can start (where relevant)

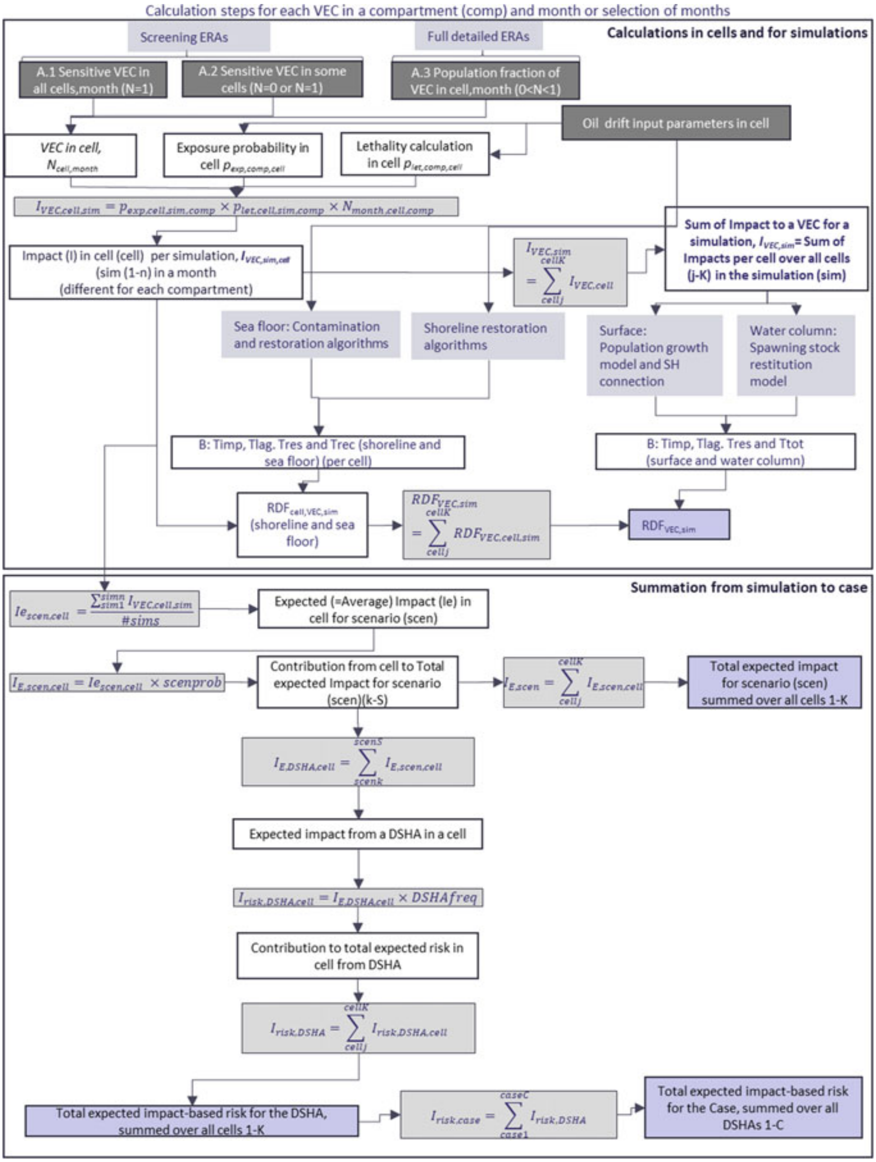

Fig. 3.3 Illustration of the impact and restoration calculations in cells and summations over all cells. Calculations in single cells and simulations (upper section) provide the most detailed options for result analysis of scenario results, whereas the summary steps from initial calculation of impact in a cell for a simulation to the sum of total expected impact for a DSHA gives results for multi-scenario DSHAs and cases. The illustration shows that many levels of calculations may be extracted and presented. (scenprob = probability for scenario, dshafreq = frequency for the DSHA)

- Restoration time (t_{res}), the re-growth time from restoration starts until the VEC is recovered.
- Recovery time (t_{rec}), the sum of the three time-factors is the total time from spill to recovered VEC.

In nature, there is no clear distinction between the time phases, as inhibition of growth and re-growth can happen simultaneously, depending on the resource in question. Much of the researched literature on restoration following historic spills do not discriminate between lag- and restoration phase (see reference lists in the background reports). However, ERA Acute offers the possibility if more knowledge exists, for the user to make an expert judgement of the division between these parameters in the input, for example if there is a known threshold for recovery. For the four compartments, different parameters and sub-models are used to calculate restoration times.

3.2.3 The Two Steps Together and the Resource Damage Factor

Figure 3.2 builds on Fig. 1.2 and illustrates how impact (population/community loss) and recovery modelling in ERA Acute have been implemented, and where within the framework the formulas are used. Impact-, lag- and restoration times are defined along the time axis. The curve illustrates the initial steep decline in impacted resource from pre-spill status, until full impact (*Imp*) is reached after t_{imp}. Impact magnitude is at its maximum until restoration can start after $t_{imp} + t_{lag}$, which is illustrated by a re-growth curve to restored status of the VEC. The area formed by the curve and timeline is the total of the impact extent and duration, as also proposed by Lein et al. (1992). Restoration modelling to determine the time factors in ERA Acute reflects different restoration mechanisms in individual compartments and/or resource groups.

For sea surface and water column, restoration modelling enables an integral function for the calculation of the geometrical area that represents the combined expression of damage extent and duration. This combined expression is called the *Resource Damage Factor* (RDF) in ERA Acute (Eq. 3.5 (for surface) and Eq. 3.17 (water column)). This factor is in line with the approach used in the NRDA for the Deepwater Horizon incident to calculate "cetacean-loss-years" (Deepwater Horizon Natural Resource Damage Assessment Trustees 2016). A simpler approach has been proposed and implemented for seafloor and shoreline to calculate the RDF. Based on the total impact to a community, and including the duration of the impact, lag and restoration times, the RDF for shoreline and seafloor is calculated using linearized expressions of decline and re-growth, given in the compartment-specific sections below (Eq. 3.9 (shoreline and seafloor)). The different formulas for calculating RDF are summarized in Fig. 3.2).

3.3 Surface Compartment Calculations

The VEC unit (N) in the sea surface compartment is a population characterized by (1) population density, (2) population distribution and (3) population size. The values in the cells are fractions (relative abundances) of the population. Seabirds, marine (or aquatic) mammals and sea turtles are assigned to different wildlife groups depending on the species characteristics related to their *individual vulnerability* to oiling (physiological sensitivity to oil) and *population vulnerability* (factors affecting the potential rate of growth and long-term population size) (Bjørgesæter and Damsgaard Jensen 2015).

3.3.1 Impact Modelling

The main impact to surface VECs is through physical contact with surface oil with subsequent effect on feather structure, insulation and buoyancy, ingestion of oil, aspiration and absorption of oil components (e.g. Deepwater Horizon Natural Resource Damage Assessment Trustees 2016; National Research Council (US) 2003). The proposed threshold levels for lethal oil film thickness (2 µm for seabirds and 10 µm for marine mammals/turtles) are derived from existing literature (Hughes et al. 1990; Jenssen and Ekker (1989, 1991a, b), Jenssen 1994; Koops et al. 2004; O'Hara and Morandin 2010; Peakall et al. 1985; Scholten et al. 1996; Stephenson 1997), different environmental risk analyses methods (French-McCay 2004, 2009; NOROG 2007; Spikkerud et al. 2006) and peer group discussions. In their comparative risk assessments as input to a relative risk methodology, Bock et al. (2018) used a lower threshold of 10 µm and an upper threshold of 100 µm.

The impact for surface VECs in a cell is proportional to the fraction of the cell covered with oil above the threshold thickness of oil and the period with harmful oil in the cell, adjusted by two individual species/species group-specific vulnerability factors (behavioral and physiological factor s); p_{beh} and p_{phy} (See Supplementary Information, Tables 1 and 2). The factors represent the likelihood of being oiled and the likelihood of lethal effect given exposure, respectively and are derived for 13 wildlife groups and 58 species based on different oil vulnerability indexes (OVI). The fraction of VEC impacted (denoted N_{let}) is calculated for the relative abundance of a defined population (N) in a grid cell i and the calculations are summarized as follows (Eq. 3.2).

$$N_{let} = \sum_{i=1}^{n} N_i - \left(1 - p_{beh} \times Cov_{TH} \times p_{phy}\right)^{T_{\exp TH}} \times N_i \tag{3.2}$$

where:

- TH is oil film thickness threshold level
- Cov is the fraction of a cell covered with oil thicker than TH

- T_{exp} is exposure time of oil thicker than TH
- p_{beh} is the probability of encountering an area with surface oil (sea surface)
- p_{phy} is the probability of lethal effects given encountering with oil above TH

An alternative equation has been derived for oil drift models that do not estimate the exposure time. This equation will result in lower impact than (Eq. 3.2) if T_{exp} > 1 day and it is therefore recommended to use an oil drift model that estimates exposure time in the cell.

3.3.2 Time Factors and Recovery Modelling

The impact time in sea surface is set to 1 year, i.e. full impact is expected to be seen within one annual cycle including a breeding season. Contamination of shoreline habitats and breeding sites used by the surface VECs may have long-term consequences that may inhibit or prolong the recovery of the population, e.g. following the Deepwater Horizon incident (In ERA Acute, this is incorporated by using the lag-time calculated in the shoreline compartment ($t_{lag,sh}$ Natural Resource Damage Assessment Trustees 2016; National Research Council (US) 2003), the relative abundance data of the species in habitats (N_{hab}) and a resource-specific sensitivity factor (SF_r) for the resource (r). The calculations are summarized in Eq. 3.3.

$$t_{lag,su} = \sum_{i=1}^{\infty} N_{hab_i} \times t_{lag,sh_i} \times SF_r \tag{3.3}$$

The restoration time is calculated based on the population loss from Eq. 3.2, using a discrete logistic growth model (Maynard-Smith and Slatkin 1973). The model estimates the relative population size N in generation t + 1 as a function of the number of individuals in the previous generation. A generic look-up table of the fundamental net reproductive rate (R) for seven wildlife groups is used to determine the growth rate and the vulnerability of the population. See Supplementary Information 1 Table 3 which includes references for the values.

$$N_{t+1} = \frac{N_t R}{1 + (aN_t)^b} \tag{3.4}$$

- R = the fundamental net reproductive rate.
- $a = (R-1)/K$, where K is the carrying capacity
- b = a factor determining the density dependence type.

The restoration time factor is defined as the period from restoration starts until the population is restored to a pre-defined level of its pre-spill baseline.

The total recovery time (t_{rec}) is the sum of impact (t_{imp}), lag (t_{lag}) and restoration time (t_{res}). Together with RDF_{su} for the sea surface it is illustrated in Fig. 3.2. For the sea surface compartment, the RDF_{SU} is calculated by Eq. 3.5:

$$RDF_{SU} = 0.5 \times t_{imp}(1 - N_0) + t_{lag} \times (1 - N_0) + \int_{t_{lag}}^{t_{res}} 1 - N(t)dt \tag{3.5}$$

where:

- t_{imp}: *Impact time*. Time until full impact is observed. This value is set to 1 year as most acute impacts are assumed to be apparent after 1 reproductive year cycle.
- t_{lag}: *Lag-time.* Time until contamination has been reduced sufficiently for restoration to begin.
- t_{res}: *Restoration tim*e. The time from restoration starts until the population/community is restored to a pre-defined level of its pre-spill status or equivalent threshold.
- N_0 is impacted population.

3.4 Shoreline Compartment

3.4.1 Impact Modelling

The shoreline impact modelling uses input from an established shoreline habitat classification ranking system, the Environmental Sensitivity Index (ESI) shoreline ranking (NOAA 2002) for each grid cell in the assessment area. The VEC input (*N*-value) to impact calculation in the shoreline compartment is the number of kilometers shoreline of a particular ESI shoreline ranking in a cell (Brude et al. 2015). The ESI classification scheme (NOAA 2002) is based on the physical and biological characteristics of the shoreline environment and factors influencing the sensitivity to oil contamination, such as shoreline slope, exposure to waves and tidal energy, substrate type, biological sensitivity restoration time and ease of cleanup. Shoreline segments with higher rankings are more sensitive, following a collective evaluation of several factors contributing to vulnerability towards oil. Segments with higher rankings are therefore more likely to be damaged by oiling. Some species may be relevant to assign as a shoreline VEC in particular life stages, but then it is the habitat that is the VEC. For example, for areas where this is relevant, turtle nesting beaches may be included as a sub-group of ESI-rank 3A, although adult turtles are exposed to oil at the surface and are a VEC in that compartment.

Based on input of data for accumulated oil on the shoreline from oil drift simulations and user-defined oil density, the volume of oil in the different ESI habitats (V_r) in the grid cell is estimated by weighting the various ESI segments by their length and by applying the Oil-Holding Capacity (OHC) (Etkin et al. 2007) related to each ESI ranking (See Brude et al. 2015 for equations). The slope associated with each ESI ranking (see NOAA 2002), the tidal range and a patchiness factor originally set at 0.2, derived from a collective assessment of the shoreline oiling of the Deepwater Horizon and Exxon Valdez oil spills (described in Brude et al. 2015) and calibrated to 0.3 in 2020 (DNV GL, Akvaplan-niva and Acona 2020), is used to calculate the impacted width (W_{imp}) of the oiled shore in each segment.

Samaras et al. (2014) used tidal range (TR) and beach slope (sl) in order to define the width of the impacted coastal zone (W_{imp}) by:

$$W_{imp,r} = \frac{\mathrm{TR}}{\sin(\mathrm{atan}\,sl)} \times 0.3 \tag{3.6}$$

The oil film thickness (T) for each ESI segment is then calculated by:

$$T_r = \frac{V_r}{L_r \times W_{imp,r}} \tag{3.7}$$

where V_r is the amount of oil stranded and L_r is the length of the shoreline (segment of ESI ranking). The total impact for each ESI ranking is then given by the total length (L) for all grid cells where the thickness is above the lethal threshold value (TH). TH used in ERA Acute is 1 mm for vegetation (herbaceous plants and trees) on ESI categories 8–10, and 0.1 mm (100 µm) for invertebrate *epifauna* living in intertidal habitats on hard substrates (based on a review by French-McCay 2009). In a recent study, Bock et al. (2018) used 100 µm (lower)/1 mm (upper for vegetation) and 10 µm (lower)/100 µm (upper) for intertidal invertebrates.

$$Imp_r = \sum_{cell} L_r | T_r \geq TH \tag{3.8}$$

3.4.2 *Time Factors and Recovery Modelling*

Experience from shoreline oiling after the Deepwater Horizon Oil Spill (DHOS) also illustrate how erosion and depositional processes of the beach cycle, seasonal wind pattern and storms to a large extent impact how oil became buried, exposed and remobilized (Michel et al. 2013). Oil is removed by natural processes (or clean-up) until the shoreline is eligible for recovery and recolonization of species. The lag phase (t_{lag}) of a shoreline after oiling can be defined as the period of oil thickness above the effect-threshold value. It is influenced by volume, oil type and weathering state, shoreline hydrodynamic energy level, OHC and intrinsic oil degradation processes. Due to the more rapid removal of oil from shorelines with high wave energy, a separate lag-phase in the damage expression is considered to be relevant for medium and low energy shorelines, while the recovery time for high energy shorelines can be based on the length of the restoration phase only. A look-up table based on hydrodynamic energy level in combination with oil type specific impacts is implemented as outlined in Table 3.2.

Table 3.2 Lag-times in shoreline types classified by energy level and main oil characteristics

Shoreline energy status (ESI)	t_{lag} (years)	Type 1 very light oils	Type 2 light oils	Type 3 medium oils	Type 4 heavy oils
High energy (ESI 1A-2B)	–	0	0	0	0
Medium energy (ESI 3A-7)	0–1	0	0	1	1
Low energy (ESI 8A-10E)	3–10	0	3	7	10

The restoration phase is defined as the period from when oiling is below the effect threshold value until vegetation and invertebrates have reached 99% of the pre-spill function. Recovery rates for shorelines after damage by oiling for modelling purposes have been reviewed in detail by French-McCay (2009). Assumed values of time to recovery (t_{rec}) for vegetation or species important for the structure of a habitat, are specific to habitat type and are based on experiences from observations of natural recovery following disturbance (including spills) and from habitat creation projects. Time for recovery of benthic invertebrates to 99% of function/pre-spill situation is shown in table Table 3.3 (Brude et al. 2015).

RDF_{SH} is calculated using the generic calculation for each ESI ranking. The unit is "kilometeryears". Usually no distinction is possible between lag and restoration

Table 3.3 Restoration -times in shoreline types—vegetation and invertebrate communities (time to 99% of pre-spill function)

Habitat type (ESI class)	Vegetation or structure (years)	Invertebrates (years)
Rocky shore (1 and 8) Exposed rocky platforms (2) Fine grained sand beaches (3) Coarse grained sand beaches (4) Mixed sand and gravel beaches (5) Gravel beaches and rip rap-structures (6) Exposed tidal flats (7 and 9)	–	3
Wetland: Emergent Marsh (10A, 10B)	15	5
Wetland: Swamp (10C, 10D)	20	5

phases in recovery studies from spills (as in French-McCay 2009), meaning that implementation of observed recovery times as restoration time in ERA Acute can be conservative when including also a lag-time before recovery can start.

$$RDF_{SH,SF} = \frac{Imp_{r,month} \times t_{imp}}{2} + (Imp_{r,month} \times t_{lag}) + \frac{Imp_{r,month} \times t_{res}}{2} \tag{3.9}$$

- t_{imp}: *Impact time*. Time until full impact is observed. This value is set to 1 year as most acute impacts are assumed to be apparent after 1 reproductive year cycle.
- t_{lag}: *Lag-time*. Time until contamination has been reduced sufficiently for restoration to begin.
- $t_{res:}$ *Restoration time*. The time from restoration starts until the population/community is restored to a pre-defined level of its pre-spill status or equivalent threshold.
- *Imp* is impacted length of coastline (km).

3.5 Water Column Compartment

3.5.1 Impact Modelling

Two different approaches are developed for ERA Acute water column impact calculations and are described in the development report by Brönner et al. (2015).

3.5.1.1 Time-Averaged THC-Max

One alternative calculation uses input of "THC_{max}" (total hydrocarbon concentration) from the oil drift simulations to calculate p_{let} in each cell, using an SSD curve (Nilsen et al. 2006). In OSCAR, this representative THC-concentration is calculated throughout the oil drift simulations, the highest THC-concentration from any of the water layers is recorded at each time-step and the final value is the average of these (time-averaged "THC_{max}"). Similar values from other reliable oil spill models may also be used, however differences in how the inputs are calculated must be observed.

The concentration is entered into a dose-response curve (Species Sensitivity Distribution (SSD)) proposed by Nilsen et al. (2006) for use in EIF Acute (Spikkerud et al. 2006). The SSD is based on a dataset compiled by the National Research Council of the National Academies (2005).

The SSD curve has a 5% effect level (LC5) of 58 ppb THC for dispersed oil in sensitive species, and a LC50 value of 193 ppb. p_{let} in each simulation and each grid cell i is given as:

$$p_{let,WC,i,sim} = \Phi\left(\left(\frac{lnx - ln193)}{0.73}\right), \mu, \sigma\right) \tag{3.10}$$

where:

- Φ: cumulative normal distribution function: with $\mu = 0$ and $\sigma = 1$
- x: target THC concentration.

3.5.1.2 Externally Calculated Lethal Fraction

In addition to the complexity of a three-dimensional compartment and varying composition of the spilled oil due to weathering processes, the main challenges for computing the impact of oil to water column organisms include the temporal variation in toxicity of the oil, as well as temporal and spatial variations in oil concentrations due to transport and weathering. This is better reflected when the potential mortality accumulates during the course of the oil drift simulations and requires access to an oil drift model that calculates an accumulated fraction of the eggs/larvae that are killed. This fraction is then used directly as p_{let}. ERA Acute allows for the results of advanced oil spill models that calculate the eggs/larvae fraction lost to be entered into the model but does not require it. Below, a description is given on how the oil spill model OSCAR calculates this potential fraction killed.

Oil in the water column is partitioned between dispersed oil droplets and water-soluble fractions (dissolved oil components). For the dissolved phase, the "fraction killed" per cell is accumulated over the time steps of the simulation using a Quantitative Structure-Activity Relationship (QSAR) between toxicity and the composition and amount of the dissolved hydrocarbons at the time step. Choice of reference oil is therefore an important driver in the result, as different oils have different hydrocarbon group compositions. Based on their molecular structure, the toxicity of the dissolved phase is calculated and the toxicity of the mix is a function of the composition of the hydrocarbon mix, as known from QSAR theory used in predictive toxicology (French-McCay 2002). This approach uses the octanol-water partitioning coefficient (K_{OW}) and the corresponding narcotic effect as the endpoint.

Time- averaged concentration and the corresponding mean composition are calculated for the actual exposure times (τ) in subsequent 96-hour periods. The exposure time is defined as the time when dissolved oil is present at a concentration > 0 in the given 96-hour period (Johansen et al. 2005).

Each component group has an LC50 value and at each time-step (in each cell) the corresponding potential lethality of the mix is calculated by a modification of Eq. 3.11 (French-McCay 2002).

$$LC50_{mix} = 1 \Big/ \sum \frac{F_j}{LC50_j} \tag{3.11}$$

where F is the fraction of the component j in the mix. The modification adjusts for exposure time (τ) by the following equation (Johansen et al. 2005);

$$LC50(\tau) = LC50_{\infty}\left[1 - \exp(-\varepsilon\tau)\right] \tag{3.12}$$

$LC50_\infty$ is the intrinsic toxicity value, which is assumed to correspond to 96 h LC50 values for each component group (Johansen et al. 2005). ε is a coefficient which expresses the exposure time dependency of the toxicity. It depends on the KOW for the given component by the equation log ε = 1.47–0.414 log KOW (French-McCay 2002).

The dose-response curve used is a log-normal Species Sensitivity Distribution (SSD) curve developed by Nilsen et al. (2006) (logarithmic SD = 0.32). The LC5 value derived from the SSD curve is used to represent LC50 for a particularly sensitive species (5th percentile most sensitive), which is used as the effect limit for dissolved components.

Based on the QSARs, the Critical Body Residue (CBR) is calculated by CBRj = BCFj × LC50j for each component group j, Bioconcentration Factor (BCF) is related to KOW (Brönner and Nordtug 2015). To calculate the actual body residue at each time step for each component, the body concentration is a result of uptake and elimination. The uptake rate is proportional to the environmental concentration C_A, while the elimination rate is proportional to the body concentration (body residue) C_B. The uptake rate is related to the size of the organism (Hendriks et al. 2001) and the lipophilic properties of the compounds which are related to the octanol/water partitioning constant (Log Kow). See Brönner and Nordtug (2015) for equations OSCAR uses to calculate this, referring to De Hoop et al. (2013) and McCarty and Mackay (1993). From the calculated body residue (CB) at the given timestep, a potential mortality is calculated by the SSD curve developed by Nilsen et al. (2006) and implemented as:

$$\text{Potential mortality, } P = (x, 0, \sigma)$$

where Φ is the cumulative normal distribution with argument x, mean value 0 and standard deviation (slope) σ, $x = \log(C_B/\text{CBR})$ or log $(\Sigma(C_{B,j}/\text{CBR}_j)$ (where j is component) and standard deviation is = 0.32. This dose-response curve is used to compute potential mortality in each grid cell at each time-step. The accumulated maximum mortality over all time steps is reported as "fraction killed" in the cell which is then used as input to ERA Acute. The maximum is a maximum of the whole water column, which may be conservative in some water layers.

This second approach in ERA Acute involves access to detailed modelling of input of potential mortality and an oil spill model that has composition information on component groups. It bears some similarities with calculation of mortalities of early life stages of fish in SYMBIOSES (SYsteM for BIOlogy-based asSESsments), which consists of several coupled models where OSCAR provides the oil spill input on component composition at each time step to LARMOD, which in turn calculates toxicity using chemical uptake kinetics and elimination rates for a given life stage. The fish ecotoxicology module calculates mortality assuming additive effects between mortalities caused by individual pseudo-components (Carroll et al. 2014, 2018).

3.5.2 Time Factors and Recovery Modelling

In the water column a lag time is not assumed, as the impact will occur within the annual spawning cycle and the oil in the water column will not be present the following year as a residual contamination.

The larvae loss is calculated as described in Sect. 3.6.1, as the maximum fraction killed summed up over all cells in the simulation to a total larval loss for that spill simulation. The total oil-induced impact (sum of all cells) (Imp_{total}) on fish eggs and larvae, representing the year class 0, is input data as a larvae loss to the restoration model, which expresses impact on the reproductive unit (spawning stock development). Two runs of the *global fish restoration model* are made, with and without oil impact to eggs/larvae, using basic parameters of population biology to calculate expected recruitment (E_{Recr}) with and without oil, relative to the average recruitment ($\text{Recr}_{\text{Average}}$). This is then used to calculate the time until the fish spawning stock is back to pre-spill status (See Brönner et al. 2015 for more detail).

Recruitment of juvenile fish from spawning product to the adult spawning stock is the result of many complex and interacting factors of both biological and oceanographic origin, and the fluctuation of recruitment success is high, resulting in strong and weak year classes. Two of the best examined fish species worldwide; Barents Sea cod (*Gadus morhua*) and capelin (*Mallotus villosus*) are used as representative for a long-lived (cod) and a short-lived (capelin) species. Research of spawning and abundance of juveniles of these two species shows that typical mortality rates in pelagic spawners are well above 99% already at the end of the larval stage (4–5 months) (Marshall et al. 2006; Eriksen et al. 2009; Huse and Gjøsæter 1997). For 0-group and juvenile fish, natural mortality continues to be high, or very high and are strongly fluctuating.

ERA Acute uses a “gate model” in restoration modeling. The gate specifies the number of surviving larvae to become recruits, rather than inducing an annual mortality. The parameter *Critical density* (default 5%) expresses the threshold for when a direct relationship is modelled between the size of the spawning stock and recruitment.

If the analyzed fish stock is above critical density, recruitment is fully independent of the size of the spawning stock (Eq. 3.13). If the analyzed fish stock is below critical density the spawning success may be too low for adequate recruitment. The model then calculates the expected recruitment relative to current spawning stock size ($\text{SS}_{\text{current}}$) and the long-term average spawning stock ($\text{SS}_{\text{average}}$) (Eq. 3.14):

$$E_{recr} = Recr_{average} \tag{3.13}$$

$$E_{recr} = Recr_{average} \times \frac{SS_{current}}{0.05} \times SS_{average}. \tag{3.14}$$

Critical oil mortality (%) represents the threshold mortality of eggs and larvae and defines the level of conservatism for the relationship between larvae mortality and reduced recruitment. If Imp_{total} < Critical oil mortality, the “gate model” is used (Brönner et al. 2015): Modelled natural survival up until recruitment is the reference level against which oil impact on eggs and larvae is measured (scientifically most valid approach). If Imp_{total}> Critical oil mortality, oil-induced mortality of larvae equals reduction in recruitment. Critical oil mortality can be set low for added conservativity.

ERA Acute, using the gate model, calculates N_i as the spawning stock size without oil impact and $N_{oil,i}$ is spawning stock size where the population in the first year was impacted by oil-induced mortality.

Recruitment modification: In the gate model, annual recruitment (E) is simulated as a modification of the potential recruitment weight (W) using probabilities (P) of periods of favorable and unfavorable conditions.

The expected value of the recruitment weight modification (E(W)) in a randomly chosen year is:

$$E(W) = [P_{unfavorable} * E(W)_{favorable}] + [P_{shift} * E(W)_{shift}] + [P_{favorable} * E(W)_{favorable}] \quad (3.15)$$

The simulated recruitment is calculated as:

$$R_1 = 1000 * [W1/E(W)],\ R_2 = 1000 * [W2/E(W)], \ldots, R_k = 1000 * [Wk/E(W)] \quad (3.16)$$

Population model: In the population model:

X_t represents the number of spawning adults in year t. Average abundance of the spawning stock is denoted E(X). Three parameters are needed in the iteration equation, and these values are different for different species depending on whether they are long-lived (cod) or short-lived (capelin) (Table 3.4):

- Annual natural mortality in percentage (m),
- age at recruitment (tr),
- age at sexual maturity (tm).

Table 3.4 Input data to the Population model used in ERA Acute for long-lived and short-lived species (Table from Brönner et al. 2015)

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

The average number of first year spawners is: E(R) × [$(1–m)^{tm-tr}$]

Average, natural mortality of adults is: X × m.

In a sustainable population, the gain (new recruits) and loss of individuals (natural mortality of adults) must balance each other, and we have that E(R) × [$(1–m)^{tm-tr}$] = E(X) × m.

The average abundance of adults (E(X)) corresponding to an average number of E(R) recruits is therefore: E(X) = E(R) × [$(1–m)^{tm-tr}$/m].

Because of the stochastic nature of recruitment, the abundance of the spawning stock at time $t + 1$ will fluctuate around this expected number of spawners according to the iteration equation:

$$X_{t+1} = [X_t \times (1 - m)] + \left[R_{t+1-(tm-tr)]} \times [(1 - m)^{tm-tr}]\right]$$

For the interested reader, the full algorithm programming guide containing 333 functions and interdependencies in given in Appendix C of Brönner et al. (2015).

Resource damage factor in the water column, RDF_{WC} is expressed as *spawning stock reduction years* (Eq. 3.17) and is calculated as sum of difference in % in the modelled spawning stock size with and without oil-induced mortality in years where difference exceeds 1%. This means that 99% of the undisturbed state is used as a threshold for the resource impact calculation, although in a fluctuating environment, natural variation will oscillate with much higher amplitude than 1%.

$$RDF_{WC} = 100 \sum_i \frac{N_i}{N_{oil,i}}, \forall_i \frac{N_i}{N_{oil,i}} > 0.01 \quad (3.17)$$

where:

- N_i is spawning stock size without oil impact.
- $N_{oil,i}$ is spawning stock size where the population in the first year was impacted by oil-induced mortality.

3.6 Seafloor Compartment Functions

3.6.1 Impact Modelling

The seafloor is divided into the sub-compartments hard bottom and soft bottom (sediment) and feeding modes are used to determine exposure route(s) for the species groups on several soft sediment substrate types (Stephansen et al. 2015). The main impact to sediment *infauna* is via exposure through interstitial water (IW) and to hard-bottom and soft substrate *epifauna* through water column using the same impact modelling as in the water column compartment. The additive effect of ingestion (Ing) is added for *epifaunal* and *infaunal* deposit feeders, where exposure is through hydrocarbons leached into gut water.

Equilibrium Partitioning Theory (EqP) is used to determine exposure to sediment-dwelling organisms (Schwartz et al. 1990; Di Toro et al. 1991; EPA 2008). With input of THC in sediment from oil drift modelling in kg/m^2, ERA Acute first calculates the concentration of THC (C_{THC}) in the sediment in ppb, using mixing depth, dry density and water content of the soft substrate type, and then calculates the partitioning of THC between sediment-bound (THC_{sed}) and bioavailable interstitial water (THC_{IW})-using inputs of octanol-water coefficients (K_{OW}) and total organic carbon (TOC) to calculate organic carbon/water partition (K_{OC}). The concentration in IW (C_{IW}) determines exposure to *infauna*.

$$C_{THC,sed,cell,sim}\left(\frac{\mathrm{mg}}{\mathrm{kg}}\right) = \frac{THC_{sed,cell,sim}\left(\frac{\mathrm{kg}}{\mathrm{m}^2}\right) \times 10^6\left(\frac{\mathrm{mg}}{\mathrm{g}}\right) \times \frac{1}{BDepth(m)} \times (1 - \mathrm{WatC})}{DryDens\left(\frac{kg}{m^3}\right)}$$

where:

- Mixing depth (BDepth): Depth of bioturbated layer in m (meters). Used to derive THC concentrations in sediments from THC/m^2
- WatC: Water content of sediment = porosity (void volume) (given as Volume fraction 0–1 where 1 = 100%)
- DryDens: Density of dry weight fraction of sediment.

$$Log_{10}K_{OC} = 0.00028 + 0.983 \times (Log_{10}K_{OW})(\text{Di Toro et al.1991})$$

where

- TOC: Concentration of TOC in habitat, is sediment (as fraction) = foc

The concentration of THC in the sediment interstitial water is calculated as:

$THC_{IW,cell,sim} = THC_{sed,cell,sim}/(foc \times Koc)$ (derived from EPA 2008 and Di Toro et al. 1991).

For deposit feeders that ingest sediment particles, partitioning between THC_{sed} and exposure in gut water (THC_{Ing}) is determined using calculated bioconcentration factors (BCF) to determine Biota-to Sediment Accumulation factors (BSAF) (Kraaij et al. 2002; (Klif) Klima- og forurensningsdirektoratet 2011).

$$\mathrm{BSAF} = \mathrm{BCF}/(\mathrm{K_{oc}} \times \mathrm{f_{oc}})$$

where: Log BCF = 0.85 × Log K_{OW} − 0.70

(See more information how this is used in Stephansen et al. 2015). The calculated exposure concentration THC_{IW} or THC_{Ing} is entered into the SSD-curve by Nilsen et al. (2006) to calculate $plet_{IW}$ and $plet_{Ing}$. For *epifauna*, e.g. corals or sponges THC_{WC} is currently used directly to determine $plet_{WC,SF}$ using an SSD-curve derived by Nilsen et al. 2006, pending improved stochastic modelling of time-averaged mortality directly in the *lower* water column using the preferred method for water column resources (see 3.6.1).

Species that ingest sediment particles are exposed both externally ($plet_{IW}$ or $plet_{WC,SF}$) and with added lethality from $plet_{Ing}$. Seven feeding modes are identified based on biological criteria, which are assigned to four essential exposure mode combinations: Exposure through water column (WC) (*epifauna*) or IW (*infauna*) and any of these with ingestion (Ing) for deposit feeders.

VEC data are prepared either as single-species data or substrate-based data community data with a feeding mode. If accurate data for distributions of feeding modes within a community can be found, it is possible to assign community VECs with a combination of fractions of feeding modes in a *community* contributing to the calculation (See Stephansen et al. 2015). For species that are partially *infaunal*, partially *epifaunal*, such as e.g. seapens, these may be ascribed an additive effect of both WC and IW exposure by using both modes to define exposure. The calculator will then summarize the two p_{let}-values to an additive effect.

3.6.2 Time Factors and Recovery Modelling

In the seafloor compartment, the time factors are included in the impact calculation for each cell and simulation before the results are summarized and statistics are presented. Impact time, t_{imp} is default set to 1 year to cover an annual cycle. For soft substrates, the lag-time, $t_{lag,sed}$ is set to 0 in the current soft substrate implementation, assuming that restoration begins next reproductive cycle.

Restoration time, t_{res} in soft substrates are calculated by a linear relationship (Olsgård and Gray 1995) implemented as Eq. 3.19, between the amount of oil in the sediment (THC_{sed}) above a threshold value ($THC_{threshold,sed}$) (currently 50 ppm, Renaud et al. 2008) and the expected maximum concentration of THC resulting from sedimentation of oil from an accidental release ($THC_{benchmark\text{-}max,sed}$). (currently 1000 ppm (Olsgård and Gray 1995). The average value of 20 years found in literature search (Renaud et al. 2008) is based on data from the North Sea (for which sandy sediments are the "standard" substrate). For VECs (substrate communities) with different recovery times than the average value of 20 years, a restoration time-modifying sensitivity factor (SF) is used to calculate t_{res} (Eq. 3.19). The value of SF is currently proposed to be calculated as the ratio of the TOC-content of the substrate relative to the TOC-content of the sand substrate for which 20 years was found to be the restoration time ("standard-substrate") (Eq. 3.18, in Stephansen and Bjørgesæter 2018). RDF is calculated from the general Eq. 3.9 shared with Shoreline.

$$SF_{substr} = TOC_{substr}/TOC_{std.substr} \tag{3.18}$$

$$t_{res,sed} = \frac{(THC_{sed} - THC_{threshold,sed})}{THC_{benchmark-max,sed}} \times 20 \times SF_{substr} \tag{3.19}$$

For hard-bottom communities, such as corals etc., a significant number of years may pass before any re-growth is seen. (Fisher et al. 2014; White et al. 2012; Hsing et al. 2013). A lag-time before recovery commences (t_{lag}) and the restoration time (t_{res}) are given in the form of input tables as functions of the impact magnitude to the coral. (See table in Stephansen et al. 2015; Background Report 6 Seafloor Compartment ERA Acute 2015).

3.7 Summarizing Impacts in Cells to Scenarios and DSHAs

As explained in Chap. 1, the smallest unit of calculations for a VEC is in each grid cell for each single oil drift simulation (Fig. 1.6).

From simulation and cell level, results can be analyzed to the total average risk for the spill scenario and DSHA. Figure 3.3 gives an overview of the main components and the available endpoints per cell, in single simulations and eventually in multi-scenario cases. Results presented in Fig. 3.3 show how the expected impacts (based on averages or weighted impacts) are calculated, where scenario probabilities and incident frequencies are included at certain steps in the calculations.

In addition to the overall summarized results, using the single simulation results in cells ($I_{VEC,sim,cell}$ in Fig. 3.3), a range of statistical results can be presented, e.g. percentile-values, maximum values, probabilities of impacts in ranges etc. All time factors are recorded as outputs and are available for separate statistics of total time to recovery. Although ERA Acute uses continuous impact and restoration functions for improved resolution over MIRA (NOROG 2007), grouping results in impact or time-factor ranges is useful, and can be plotted in risk matrices against scenario probabilities or DSHA frequencies. Calculations in single cells and simulations (upper section, Fig. 3.3) provide the most detailed options for result analysis of scenario results. Summary steps from initial calculation of impact in a cell for a simulation, up to the sum of total expected impact for a DSHA (lower section) gives results for multi-scenario DSHAs and cases. The illustration in Fig. 3.3 shows that many levels of calculations may be extracted and presented.

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Chapter 4
Testing and Validating Against Historic Spills

Abstract To validate the predictive capability of ERA Acute, a study was carried out using data from two well-studied historic oil spills, the Exxon Valdez Oil Spill (EVOS) and the Deepwater Horizon Oil Spill (DHOS) incidents. Results from the case studies with ERA Acute were compared to the impact estimates and recovery observations that have been reported in the extensive research following the two incidents. Resource data relevant for each of the two incidents were reconstructed within the analysis area. Performance boundaries were set up for evaluating the ERA Acute results, based on the ranges of the impact and recovery estimates reported in the post-spill assessments. Validation of an oil spill ERA model against post-spill assessments of historic spills is a challenging exercise due to scientific limitations of both. ERA Acute performed satisfactorily compared to the performance boundaries and the study gave useful insight into the predictive capabilities of ERA Acute. The results from the study were used to evaluate between two different impact models and to increase the individual vulnerability of cetaceans.

Keywords Model validation · ERA Acute validation · ERA Acute case studies · Impact validation · Exxon Valdez oil spill · Deepwater Horizon oil spill

4.1 Method of Validation Against Historic Spills

An ERA Acute assessment has been performed for two historic oil spill incidents. The study was performed according to the standard procedure of a regular environmental risk analysis (ERA) for exploration wells on the NCS (OLF 2007) using the ERA Acute methodology (cf. Fig. 1.6). The aim of the assessment was to compare ERA Acute results with damage estimates from post spill assessments from historic oil spill incidents, where such estimates are derived from observed and reported impacts. Required input data to perform the validation study were: (1) analysis areas and grids, (2) damage assessment from field observations, (3) pre-defined performance boundaries (4) oil drift statistics from stochastic modelling and field observation, (5) VEC datasets.

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https://doi.org/10.1007/978-3-030-70176-5_4

The Deepwater Horizon oil spill and Exxon Valdez oil spill were selected as case studies for comparing results from ERA Acute against historic spills.

- The Deepwater Horizon Oil Spill (DHOS) began on 20th April 2010 in the Gulf of Mexico on the BP operated Macondo Prospect. Following the explosion and sinking of the Deepwater Horizon oil rig, a seafloor oil gusher flowed for 87 days, until it was capped on 15th July 2010. The US Government estimated the total discharge to be approximately between 701,000 to 857,000 m^3 crude oil (US Coast Guard 2011).
- The Exxon Valdez Oil Spill (EVOS) occurred 24th March 1989, when the tanker Exxon Valdez ran aground on Bligh Reef in Prince William Sound, Alaska. The vessel was traveling outside normal shipping lanes to avoid ice. Within six hours of the grounding, the Exxon Valdez spilled approximately 40,000 m^3 Prudhoe Bay crude oil (Exxon Valdez Oil Spill Trustee Council, https://www.evostc.state.ak.us/index.cfm?FA=facts.details).

The comparison studies between the results of the ERA Acute analyses of the two cases and the post-spill estimations of damages were part of the process of validating ERA Acute as a method suitable for ERA purposes. Quantitative comparison studies against historical oil spills are not commonly performed for environmental risk assessment methods but have been performed for e.g. the biological effects model in SIMAP oil spill model (French-McCay, 2004; French and Rines, 1997). Following an evaluation of data availability and quality, the EVOS and DHOS cases, limited to surface and shoreline compartments, were chosen for comparison. ERA Acute impact calculations were compared to injury estimates from post spill assessments. For the sea surface compartment, both modelled and satellite oil drift data were used in the study.

4.1.1 Analysis Areas

The analysis area for the DHOS case was set to cover the US Economic Exclusion Zone (EEZ) of the Gulf of Mexico (Fig. 4.1). The area is represented by 10,792 surface grid cells of 10 × 10 km (cells containing water) covering approximately 1,014,789 km^2 sea surface area, divided into 188,989 km^2 coastal area (<40 km from the coastline) and 825,800 km^2 offshore area (>40 km from the coastline).

The analysis area for the EVOS case was divided into the two areas, one that covers the total impact area including Cook Inlet, Kenai Peninsula, Kodiak Island and Alaska Peninsula and one that covers the Prince William Sound (Fig. 4.2). The Prince William Sound is represented by 240 surface grid cells of 10 × 10 km overing approximately 14,592 km^2 sea area. The analysis area for seabirds and marine mammals was restricted to the Prince William Sound since the VEC dataset and injury assessment estimates were most reliable in this area.

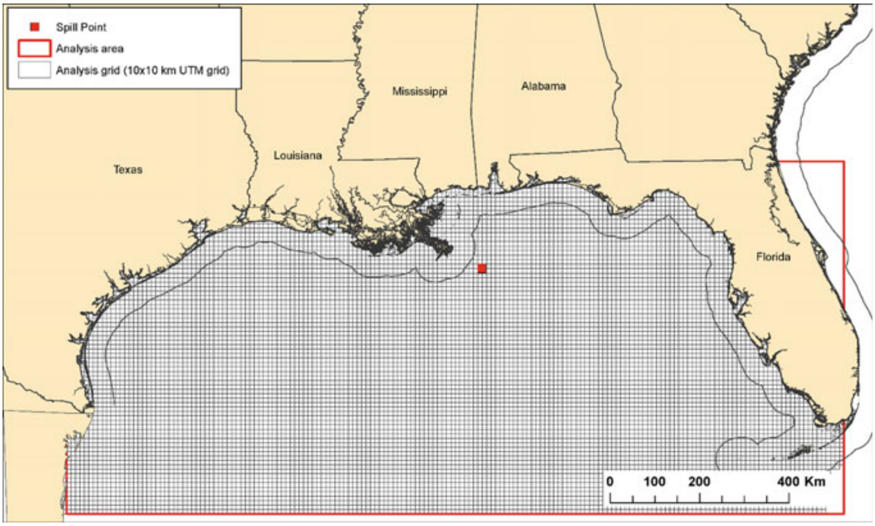

Fig. 4.1 Study area and 10 × 10 km UTM-grid used in the analysis for the Deepwater Horizon Oil Spill

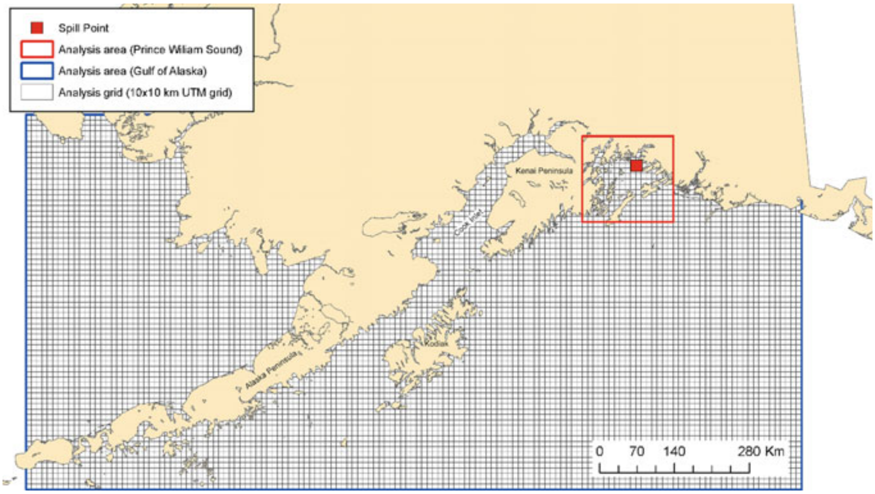

Fig. 4.2 Study areas and 10 × 10 km UTM-grid used in the analysis for the Exxon Valdez Oil Spill

4.1.2 Construction of Performance Boundaries

To evaluate the performance of ERA Acute, we defined *performance boundaries* based on field-based injury assessments and compared these with the impact and long-term damage calculated with ERA Acute. The main sources of information and

Table 4.1 The performance boundaries used to evaluate the performance of the biological impact models for seabirds, marine mammals, sea turtles and shoreline in ERA Acute for the Deepwater Horizon Oil Spill case

Valuable ecosystem component		Unit	Acute mortality and impact			
Group	Species		Threshold low	Limit low	Limit high	Threshold high
Seabirds	"All"	Individuals	8,500	56,141	900,000	1,000,000
Marine mammals	Bottlenose dolphin	Individuals	870	2,046	14,222	16,845
	Bryde's whale	Individuals	0.6	0.8	9.5	11.9
Sea turtles	Kemp's Ridley	Individuals	1,575	2,100	3,100	3,875
	Loggerhead	Individuals	1,650	2,200	3,600	4,500
Shoreline	Flora	Km	563	1,161	2,117	3,307
	Fauna	Km	704	1,451	2,646	4,134

Beyer et al. (2016); Deepwater Horizon Natural Resource Damage Assessment Trustees (2016); Haney et al. (2014a), (b), (2015), Lockyer and Morris (1990); Sackmann et al. (2015)

data were the injury assessments performed during the Natural Resource Damage Assessment s (NRDAs) process following the Deepwater Horizon and Exxon Valdez oil spills incidents, respectively and in the literature (cf. Table 4.1, Table 4.2 and Supplementary Information 1 for references).

The conceptual outline of the performance boundaries is illustrated in Table 4.3 and the values used in this study for the DHOS and EVOS cases are presented in Tables 4.1 and 4.2. The green circle is the mean impact estimated by ERA Acute from a single oil drift simulation and 500 Monte Carlo simulations. The Monte Carlo simulations are performed in three steps (cf. Fig. 5.1):

(1) assigning a probability distribution to the model parameters,
(2) drawing random values from the distribution and
(3) calculating the impact.

This is repeated 500 times per VEC dataset, resulting in either 500, 1500 or 2000 estimates of impact per VEC (cf. Sect. 4.1.4). The error bars are the 95% "credible interval" and represent the uncertainty in model parameters and natural variation in density and/or distribution of the VECs (cf. Sect. 4.1.4). The credible interval is analogous to confidence intervals and is used here to emphasize that the intervals are calculated on simulated and not measured data.

The estimates falling within the different boundaries are counted and summed up to give the percentage performance for one oil drift simulation. An example of this is illustrated for oil drift simulation No. 16 in Fig. 4.3.

Table 4.2 The performance boundaries used to evaluate the performance of the biological impact models for seabirds, marine mammals and shoreline in ERA Acute for the Exxon Valdez Oil Spill case

Valuable ecosystem component		Unit	Acute mortality and impact				Recovery	
Group	Species	Individuals	Threshold low	Limit low	Limit high	Threshold high	Low	High
Seabirds	Common murre	Individuals	1,176	3,075	15,918	23,877	10	13
	Pigeon guillemot	Individuals	135	500	1 500	2,250	Not recovering due to extrinsic factors	
Marine mammals	Harbor seal	Individuals	152	227	377	452	1	17
	Killer whale	Individuals	2	14	25	29	25	Not recovering
	Sea otter	Individuals	493	500	5,000	7,500	21	25
Shoreline	Flora	Km	20	39	185	340	3	25
	Fauna	Km	86	165	788	1,446		

Exxon Valdez Oil Spill Trustee Council (EVOSTC) EVOSTC (2010), EVOSTC (2013), EVOSTC (2014), Piatt et al. (1990), Piatt and Ford (1996), ECI (1991), Piatt and Anderson (1996), Sanger and Cody (1994), Frost and Lowry (1994), Hoover-Miller et al. (2001), Ballachey et al. (1994), Garrott et al. (1993), Garshelis (1997), Udevitz et al. (1996), Gundlach et al. (1991)

Table 4.3 Densities used to derive resource datasets for seabird in coastal areas (<40 km from land) and at open sea (>40 km offshore) in the DHOS analysis area

Density[a]	Coastal (ind./km^2)		Open sea (ind./km^2)		Distribution
	Mean	SD	Mean	SD	
Density 1	1.53	2.30	0.56	0.84	Log-normal
Density 2	3.60	5.40	1.6	2.40	
Density 3	6.60	9.90	1.6	2.40	
Density 4	9.40	14.10	1.6	2.40	

[a]Deepwater Horizon Natural Resource Damage Assessment Trustees (2016), Tasker et al. (1984), McFarlane and Lester (2005), Hess and Ribic (2000) cited in Haney et al. (2014b)

The red lines are referred to as “thresholds” and model results falling below or above these boundaries are lower or higher than the damage estimates from post spill assessments, typically by 25%. The black dotted lines are referred to as “limits”. Model results falling within the low and high limits are regarded as valid while model results falling outside the limits are regarded as satisfactory but uncertain. The results from Simulation No. 16 would be characterized as somewhat conservative and possibly even too conservative. Since different data sources are used to derive the thresholds and limits, the limit range may vary considerably and this, together with the availability and quality of input data must be taken into consideration when interpreting the results.

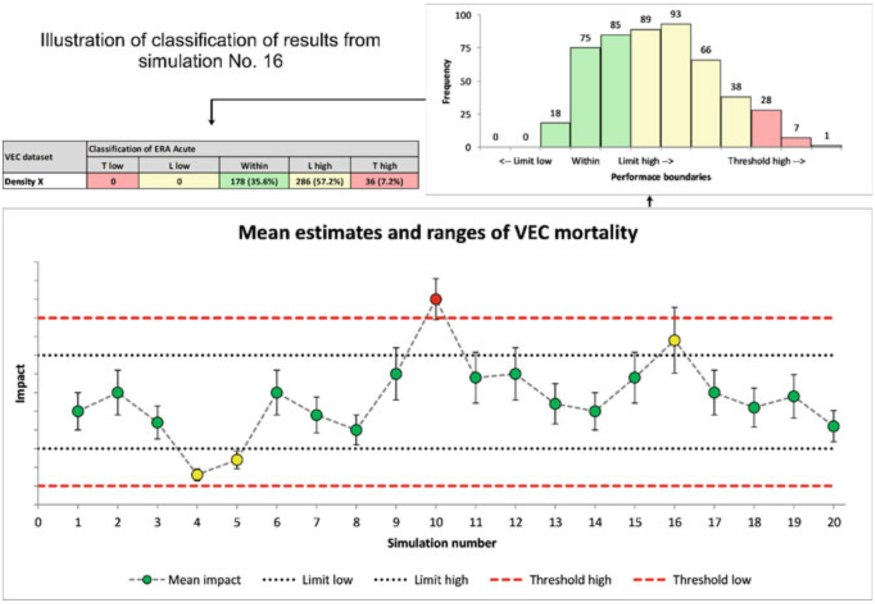

Fig. 4.3 Illustration of impact on a surface resource estimated from 20 oil drift simulations and how the estimated impacts place themselves according to boundaries derived from reported injury from the Natural Resource Damage assessments after the Deepwater Horizon, Exxon Valdez oil spill and in the literature

A stochastic approach was used to construct oil endpoint parameters to the ERA Acute models (see Sects. 1.5.1 and 4.1.3). We performed 20 oil drift simulations using OSCAR with different start dates within the seasonal time window of the two oil spills (April and May, 2001–2010 DHOS and March and April, 2006–2010 for EVOS). The differences between the estimated mean impacts (dots) in Fig. 4.3 are a result of different wind and current conditions resulting in variation in spreading, transport and weathering of the oil slicks. It is not the result of variations in the impact calculations in ERA Acute. For the DHOS case, we also tried to, by manually preparing oil spill input for ERA Acute, replicate the actual spreading and transport of the oil spill using information from field surveys and satellite data (cf. Sect. 4.1.3).

4.1.3 Reconstruction of the Oil Spills in the Analysis Areas

4.1.3.1 Oil Spill Modelling Approach

The oil spills were modelled with OSCAR (Oil Spill Contingency And Response) v.8.0 software (SINTEF 2016). OSCAR is a three-dimensional dynamic oil trajectory and chemical fates model that computes and records the distribution of oil on the sea surface, along the shorelines, in the water column and on the seafloor.

A total of 20 single simulations were performed with start dates within the seasonal time window of the two oil spills. A single simulation was performed for the DHOS case to obtain concentration of oil in the sediment. All oil drift simulations extended for 20 days after the release had been stopped.

4.1.3.2 Satellite Data Approach

The trajectory for the DHOS was reconstructed based on field surveys and satellite datasets. For the sea surface we used the dataset "*Predictive Model Cumulative Surface Oil Extent (PDARP)*" (NOAA 2017). The dataset included daily prediction of surface oil coverage from a period of 90 days with satellite observations between 23rd of April and 11th of August 2010. The data were mapped onto the UTM grid file for the DHOS and the time averaged coverage and exposure time for each 10 × 10 km grid cell in the analysis area was calculated.

The time averaged coverage for the whole period was calculated as:

$$Time\,averaged\,coverage = \frac{1}{n \geq 1} \times \sum_{i=1}^{n} \frac{\sum_{i=1}^{k} Coverage}{k} \tag{4.1}$$

where $n \geq 1$ is the number of 10 × 10 km grid cells with observed oil during the 90-day time period, k is the number of predictions of coverage from satellites within a 10 × 10 grid cell.

The exposure time is estimated as the number of days any given 10 × 10 grid cell was oiled during the 90 days of satellite observations. The maximum value is 66 days (five cells). The thickness of the oil slick is not known. In this study it is assumed that the thickness is above the threshold thickness for the VECs of interest (i.e. >2 and 10 μm).

4.1.4 Reconstruction of Resource Data in the Analysis Areas

A challenge in field validation studies is to reconstruct the pre-spill distribution and population size of the natural resource data in the study area. Three main techniques and data sources were used to construct dataset for surface VECs: (1) Monte Carlo Simulations, (2) extrapolation from field survey transects and (3) habitat density models. Monte Carlo Simulations were also used to represent uncertainty in the model parameters and to derive 95% credible intervals (cf. Sect. 4.1.4).

A brief description and examples of each type of dataset is given below.

Surface resource datasets

Three methods were used to estimate VEC densities and construct resource data sets used in the ERA Acute modelling. The two first methods were used for the DHOS incident and the third for the EVOS incident. Different methods are used based on different availability of suitable datasets.

The first method used estimates of VEC densities in the study area (Deepwater Horizon Natural Resource Damage Assessment Trustees 2016; Haney et al. 2014a, b) combined with probability distributions and Monte Carlo Simulations. Different densities and probability distributions were used for distinct habitat types within the study area. Each density and habitat were assigned a log-normal distribution with a standard deviation equal to 1.5 times the density (mean). The distribution of organisms in the environment is often log-normal and in most plant and animal communities, the abundance of species follows a (truncated) log-normal distribution (e.g. Limpert et al. 2001). A random number was drawn from the probability distribution, representing the abundance of the VEC in that cell. The same process was repeated until all grid cells in the study area were filled, and then repeated 500 times for each density (D). The densities used are given in Fig. 4.3 and an illustration of the distribution is given in Fig. 4.4.

The second method used datasets constructed by ecologists based on long term census (surveys) in the oil spill area (and season) and further processed using oceanographic and biological covariates to extrapolate abundance to areas not surveyed. These datasets are similar to the standardized VEC dataset used in ERAs on the Norwegian Continental Shelf today. The dataset for common bottlenose dolphin (*Tursiops truncatus*) is illustrated in Fig. 4.5. The dataset is derived by Marine Geospatial Ecology Laboratory/Duke University, based on habitat-based cetacean density models for the U.S. Atlantic and Gulf of Mexico (2015 Version). It is the first cetacean density map for these regions to be published in the peer-reviewed literature (Roberts et al. 2016). The abundance in each grid cell is given as the 5-percentile (P_5), mean (P_{50}) and the 95-percentile (P_{95}).

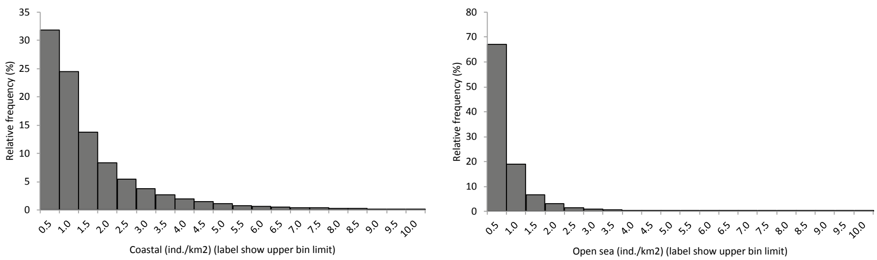

Fig. 4.4 Distribution of density in grid cell in the DHOS analysis area in coastal (left) and at open sea (right) using Density 1 in Table 4.3. The x-axis is cut-off at 10 individuals per km^2

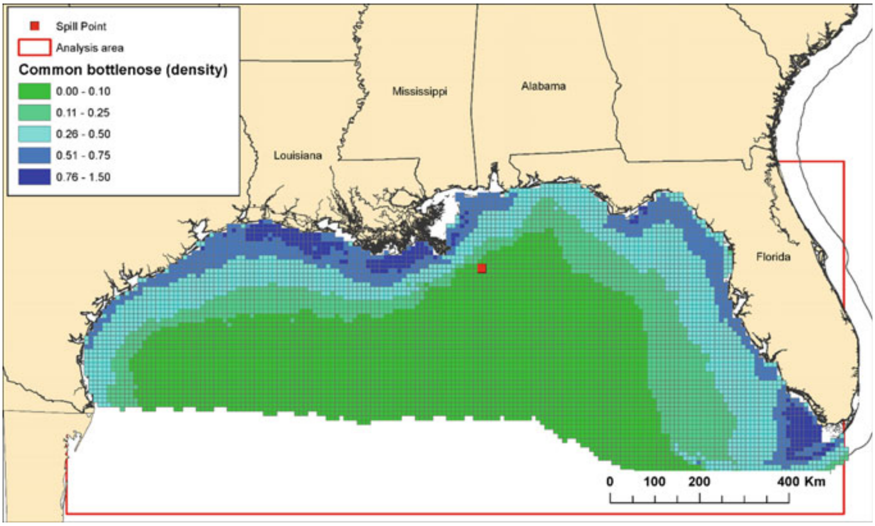

Fig. 4.5 Surface VEC datasets for the common bottlenose dolphin constructed from the habitat-based cetacean density models. *Source* Roberts et al. 2016

The third method uses the North Pacific Pelagic Seabird Database (NPPSD) (Drew et al. 2015) to construct resource dataset for surface VECs. The database includes more than 350,000 survey transects that were designed and conducted primarily to census seabirds but also includes data of several marine mammals. Transect areas and number of individuals during a transect were used to derive the distribution and density in each grid cell in the study area. The density was multiplied with the total area with suitable habitat in the grid cell (defined as cells containing seawater) and normalized against the estimated pre-spill population size of the VEC in the study area. The dataset for sea otter (*Enhydra lutris*) in Prince William Sound is illustrated in Fig. 4.6.

Vulnerability factors: A triangular probability distribution was selected to represent the uncertainty in the individual behavior factors, p_{beh} and physiological factors p_{phy} (Table 4.4). Seabirds in the Gulf of Mexico in May, June and August are dominated by surface feeding seabirds. The minimum, mode (the most likely value) and maximum values for birds in coastal habitats and open sea habitat were set equal to the estimates for coastal surface feeding seabirds (Wildlife Group 4) and pelagic surface foraging seabirds, respectively (Wildlife Group 2). For the other VECs, species or wildlife group specific values were used.

Shoreline resource datasets

ESI shoreline ranking data for the US coast of Gulf of Mexico and Alaska were downloaded from NOAA (https://response.restoration.noaa.gov/maps-and-spatial-data/download-esi-maps-and-gis-data.html). Post processing of these data included summary of shoreline length per ESI ranking in each 10 × 10 km UTM grid cell. For

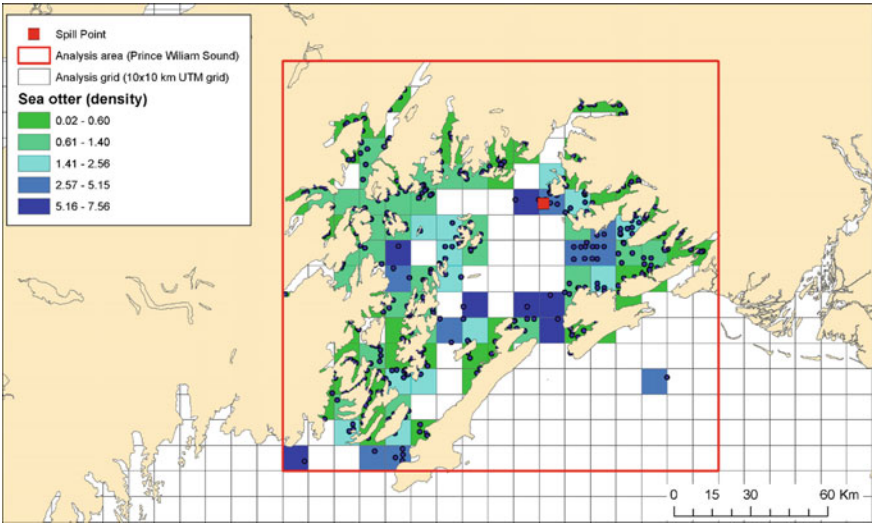

Fig. 4.6 Surface VEC datasets for sea otter constructed from the North Pacific Pelagic Seabird Database (NPPSD) in the EVOS analysis area. *Source* Drew et al. 2015

Table 4.4 Behavioral (p_{beh}) and physiological (p_{phy}) factors representing the likelihood of being oiled and the likelihood of lethal effect given exposure, and the parameters for the triangular distribution used to represent uncertainty in the Monte Carlo Simulations

VEC group	Case	VEC	Behavioral factor p_{beh}			Physiological factor p_{phy}		
			Min	Mode	Max	Min	Mode	max
Seabirds	DHOS	Seabirds—coastal	0.31	0.33	0.89	0.800	0.900	1.000
		Seabirds—open sea	0.31	0.45	0.89	0.800	0.900	1.000
	EVOS	Common murre	0.79	0.80	0.89	0.800	0.900	1.000
	EVOS	Pigeon guillemot	0.67	0.68	0.76	0.800	0.900	1.000
Marine mammals	EVOS	Harbor seal	0.83	0.90	0.96	0.004	0.028	0.058
	EVOS	Sea otter	0.79	0.88	0.97	0.500	0.720	0.930
	DHOS	Common bottlenose dolphin[a]	0.800	0.90	1.00	0.040	0.080	0.120
	DHOS	Bryde's whale[a]	0.70	0.79	0.88	0.025	0.050	0.075

[a]The values of the factors were calibrated during this study. See Sect. 4.2.1.2 for details

grid cells with extensive coverage of marsh/wetland (>100 km), a limit was set to 100 km per grid cell in order to capture the essential outer coastline reachable by oil in the oil spill model. The major shoreline habitat types in the Gulf of Mexico datasets are salt-, brackish- and freshwater marshes and swamps (ESI 10ABE) and the major shoreline types along the coast of Gulf of Alaska is gravel beaches, riprap (cobbles

Table 4.5 Overview of shoreline habitats used in this study. The shoreline habitat is more susceptible to damage by oiling with increasing ESI numbers

ESI	DHOS		EVOS		Description of ESI category
	km	%	km	%	
ESI1	133	0.8	1 888	11	Exposed rocky shores, exposed, solid man-made structures, exposed rocky cliffs with boulder talus base
ESI2	14	0.1	1 900	11	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	956	5.8	266	2	Fine to medium-grained sand beaches, scarps and steep slopes in sand, tundra cliffs
ESI4	12	0.1	137	1	Coarse-grained sand beaches
ESI5	161	1.0	3 110	18	Mixed sand and gravel beaches
ESI6	406	2.5	3 609	21	Gravel beaches, riprap (cobbles and boulders)
ESI7	555	3.4	259	2	Exposed tidal flats
ESI8	507	3.1	3 442	20	Sheltered scarps in bedrock, mud, or clay, sheltered riprap, sheltered rocky rubble shores, peat shorelines
ESI9	158	1.0	319	2	Sheltered tidal flats, vegetated low banks, hypersaline tidal flats
ESI10 ABE	11 851	72.5	1 985	12	Salt- and brackish-water marshes, freshwater marshes, swamps
ESI10 CD	1 599	9.8	0	0	Scrub-shrub wetlands, mangroves, Inundated low-lying tundra
Total	16 353	100	16 915	100	

and boulders) (ESI 6) (Table 4.5). Wetlands and marshes etc. are most widespread in Louisiana around the Mississippi River Delta while gravel beaches are scattered throughout the analysis area in PWS (Table 4.7).

4.2 Results of the Validation

4.2.1 Oil Drift

There were large differences in swept areas estimated from the oil drift model and from the oil drift constructed from satellite data in the Gulf of Mexico (Table 4.6). The modelled oil slicks ($n = 20$) on the surface cumulatively covered an area between 42,615 and 165,105 km^2. The mean area of oil thicker than 2 μm (oil slicks assumed to be harmful for seabirds) was 120,492 km^2 (range 56,944–165,105 km^2) and the mean area of oil thicker than 10 μm (oil slicks assumed to be harmful for marine mammals) was 90,302 km^2 (range 42,615–125,864km^2).

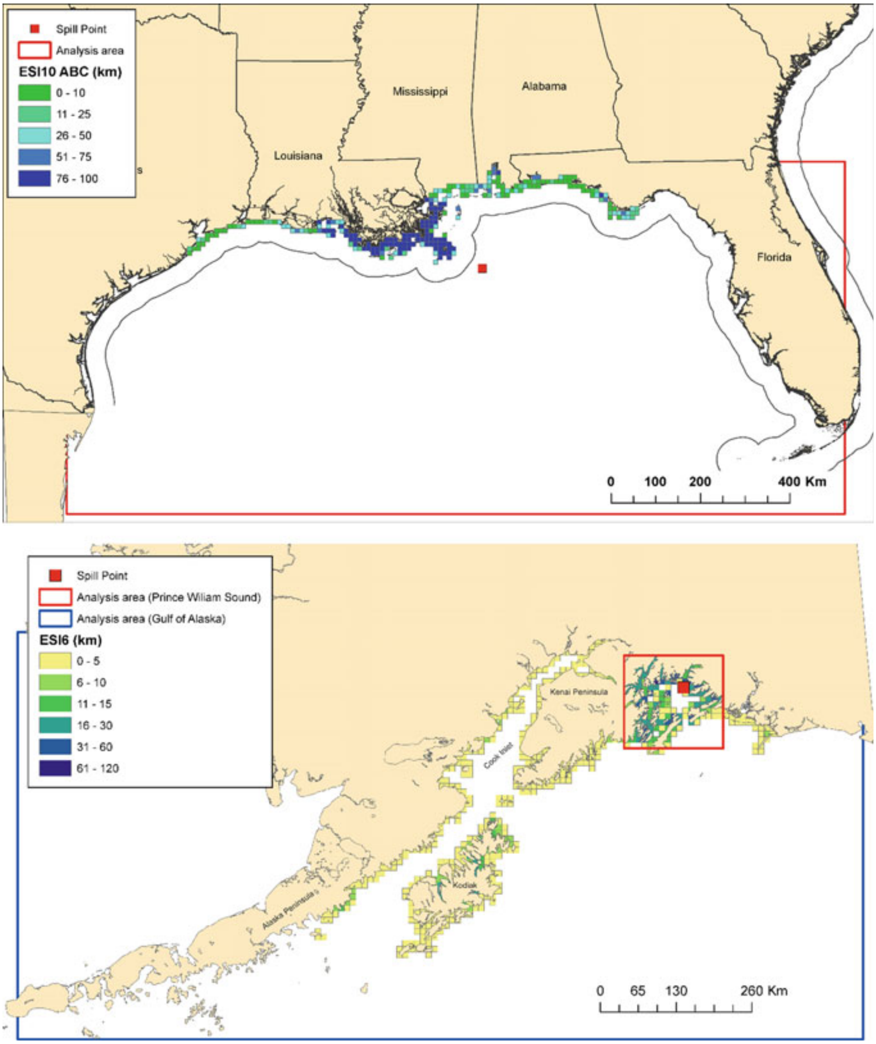

Fig. 4.7 Maps of shoreline habitat classified ESI 10ABE in the Gulf of Mexico VEC dataset (top) and ESI6 along the coast of the Gulf of Alaska (bottom)

This is within the range of the estimation of at least 112,115 km^2 by the Deepwater Horizon Natural Resource Damage Assessment Trustees (2016) but on the high side compared to the cumulatively swept area of oil slicks constructed by the satellite data. The largest differences between the modelled and observed data is the exposure time, with an overall mean of 1.2 and 1.0 days in the modeled data versus 11.8 days in the satellite data, respectively.

A comparison of the cumulative oil slick constructed from the satellite data with a deterministic simulation (Simulation No. 19 with start date 4th of March 2010) is

Table 4.6 Selected exposure statistics (mean, standard deviation) for the 20 probabilistic runs for the Deepwater Horizon Oil Spill and satellite data

Exposure statistics	Modelled data (n = 20)		Satellite data (n = 1)
	T = 2 μm	T = 10 μm	
Number of 10 × 10 km cells	5,309 (1,703)	5,155 (1,730)	2,013
Swept area (km^2)	120,492 (38,209)	90,302 (28,634)	58,578
Exposure time (days)	1.2 (0.2)	1.0 (0.2)	12.0

illustrated in Figs. 4.8 and 4.9. The modelled data (without use of oil spill response measurements) cover a larger area but with more variable coverage of oil in the cells and considerably shorter exposure time.

An illustration of accumulated oiling along the shoreline (from the same simulation) and data derived using Shoreline Cleanup Assessment Technique (SCAT) as part of the NRDA process (Nixon et al. 2016; NOAA 2017) is shown in Fig. 4.10. The modelled data show highest amount of beached oil in areas classified as "heavier oiling" (cf. Nixon et al. 2016) but also predict beaching in areas with no observed oil in the NRDA.

Differences between modelled and observed oil drift trajectory is expected due to uncertainty in the model and parameters, input data such as oil type and wind and current conditions. The extensive response to the oil spill is also likely to account for some of the differences in extent and area between the modelled and observed spreading of oil.

4.2.2 Acute Mortality in the Surface Compartment

A summary of estimated acute mortality for VECs in the surface compartment is presented in Table 4.7. The table lists the mean with two percentiles, the performance boundaries used to evaluate the results and the percentage of the simulations within each boundary. The performance varies between the different animal groups (seabirds and marine mammals) and between modelled (M) and field (F) oil drift data.

4.2.2.1 Seabirds

The estimated ERA Acute mortality with modelled oil drift data showed that on average 70% (range 61–100%) of the simulations resulted in mortality in the "within" category, 5% (range 0–16%) below the "limit low" and 24% (range 0–36%) above "limit high". No simulations yielded mortality below the "threshold low" and 1% above the "threshold high". The estimated ERA Acute mortality for seabirds with

Table 4.7 Estimated mortality with ERA Acute, the performance boundaries and classification of the estimated impacts for VECs in the surface compartments according to the performance boundaries. The number are given as percentage of the simulations falling within the different performance boundaries rounded to nearest whole number. M is modelled oil drift data and F is field (satellites) oil drift data. The number for cetaceans is based on the calibrated values for p_{beh} and p_{hy} (cf. Sect. 4.2.1.2)

Group	Species	Case	Oil drift data	Estimated mortality with ERA acute			Performance boundaries				Classification of ERA acute				
				Mean	$P_{2.5}$	$P_{97.5}$	T low	L low	Within	L high	T low (%)	L low (%)	Within (%)	L high (%)	T high (%)
Sea birds	Seabirds, four densities	DHOS	M	148,576	31,497	314,540	8,500	56,141	900,000	1,000,000	0	16	84	0	0
			F	273,753	82,279	484,625					0	0	100	0	0
	Common murre	EVOS	M	12,818	4,821	20,826	1,176	3,075	15,918	23,877	0	0	65	35	0
	Pigeon guillemot	EVOS	M	1,411	859	2,253	135	500	1,500	2,250	0	0	61	36	3
Marine mammals	Common bottlenose dolphin	DHOS	M	1,175	447	2,673	870	2,046	14,222	16,845	31	62	6	0	0
			F	9,796	6,256	14,092					0	0	98	2	0
	Bryde's whale	DHOS	M	0.3	0.0	1.1	0.6	0.8	9.5	11.9	80	16	3	0	0
			F	7.0	1.8	16.0					0	0	69	8	23
	Harbor seal	EVOS	M	195	28	685	152	227	377	452	35	37	17	6	5
	Sea otter	EVOS	M	2,374	1,205	3,997	493	500	5,000	7,500	0	0	100	0	0

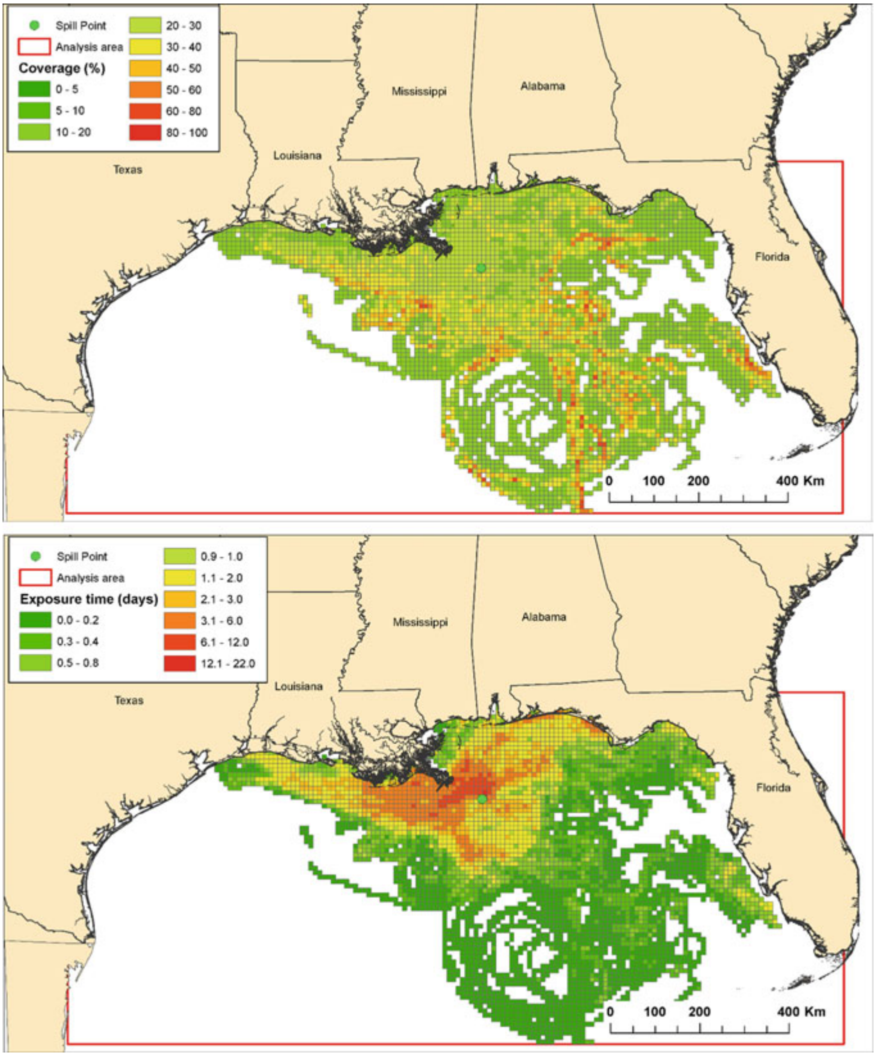

Fig. 4.8 The cumulative oil slick of the Deepwater Horizon Oil Spill derived from simulation No. 19. The color codes show the coverage of oil above thicker than 2 μm (top) and exposure time (bottom). Note that the classification of exposure time differs from the legend in Fig. 4.7

modelled oil drift data results in comparable values, and somewhat high estimates in comparison with the performance boundaries for the EVOS (Table 4.7 and Fig. 4.11).

The injury estimates for seabirds for DHOS vary considerably in the literature. The NRDA process estimated a mortality of 56,141–102,399 individuals (cf. Table 4.4.7–3 in Deepwater Horizon Natural Resource Damage Assessment Trustees 2016) while Haney et al. (2014a, b), using a carcass sampling model and an exposure probability model, estimated 600,000–800,000 individuals as a most likely value. The estimated

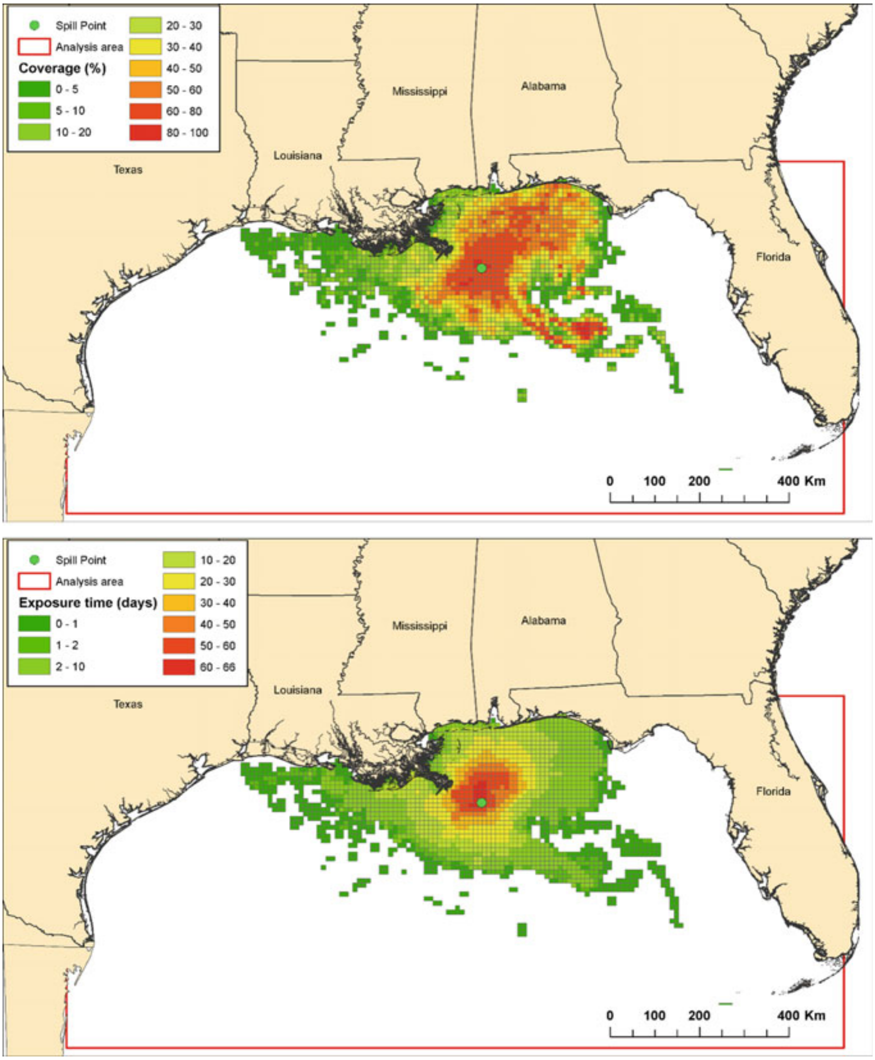

Fig. 4.9 The cumulative oil slick of the Deepwater Horizon Oil Spill derived from simulation field data (satellite). The color codes show the coverage of oil assumed to be thicker than 10 µm (top) and the exposure time (bottom). Note that the classification of exposure time differs from the legend in Fig. 4.8. *Source* Predictive Model Cumulative Surface Oil Extent (PDARP) (NOAA 2017)

ERA Acute mortality with modelled oil drift data in this study was 148,576 with a 95% credible interval (CI) of 31,497–314,540. This is a higher estimate range than the official NRDA estimates but lower than the mortality estimated by Haney et al. (2014a, b).

The estimated ERA Acute mortality with oil drift statistics derived from satellite data generated on average 1.8 times higher acute mortality than calculations based

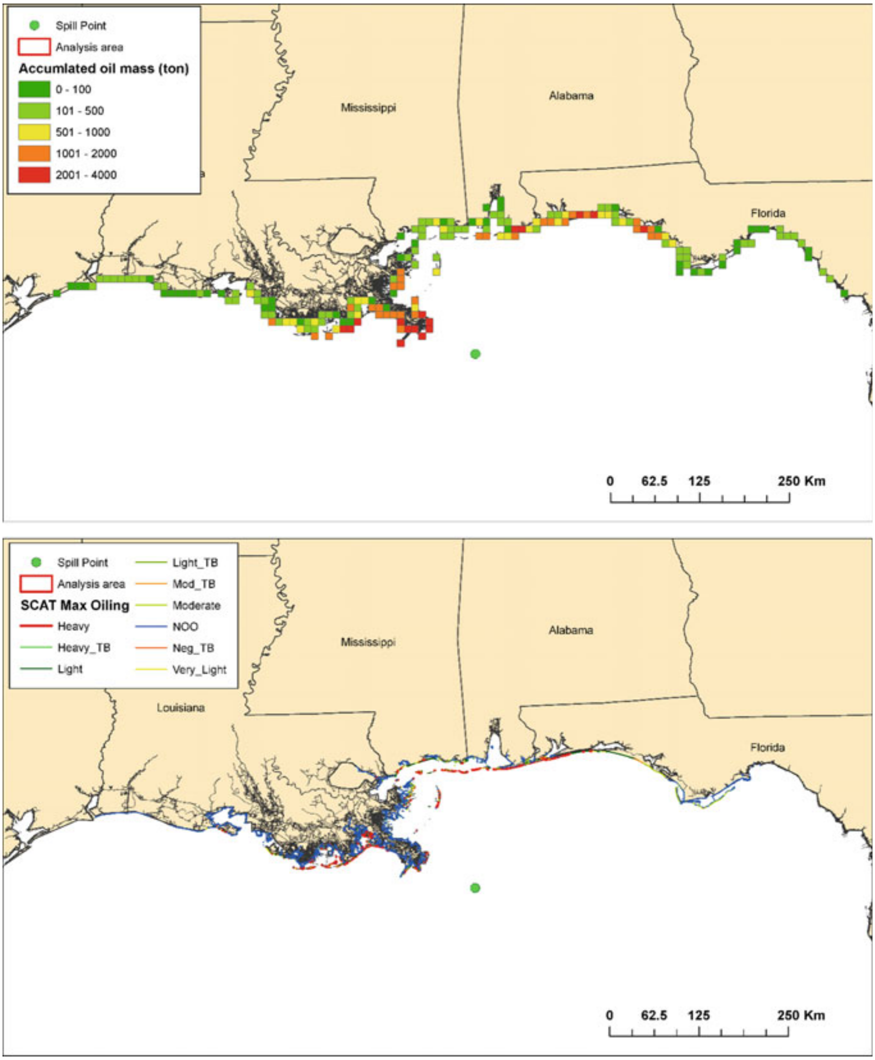

Fig. 4.10 Map showing accumulated oiling along the shoreline for the Deepwater Horizon Oil Spill derived from simulation No. 19 (top) and an illustration of shorelines classified by final oil exposure categories for beaches, coastal wetland and other shoreline habitats (bottom). See Nixon et al. (2016) and NOAA (2017) for original and detailed maps. NOO = No Observed Oil. Sources: ERMA Layer: 11-Nov-10 Mobile SCAT Maximum Oiling and ERMA Layer: 23-Jan-11 Houma SCAT Maximum Oiling

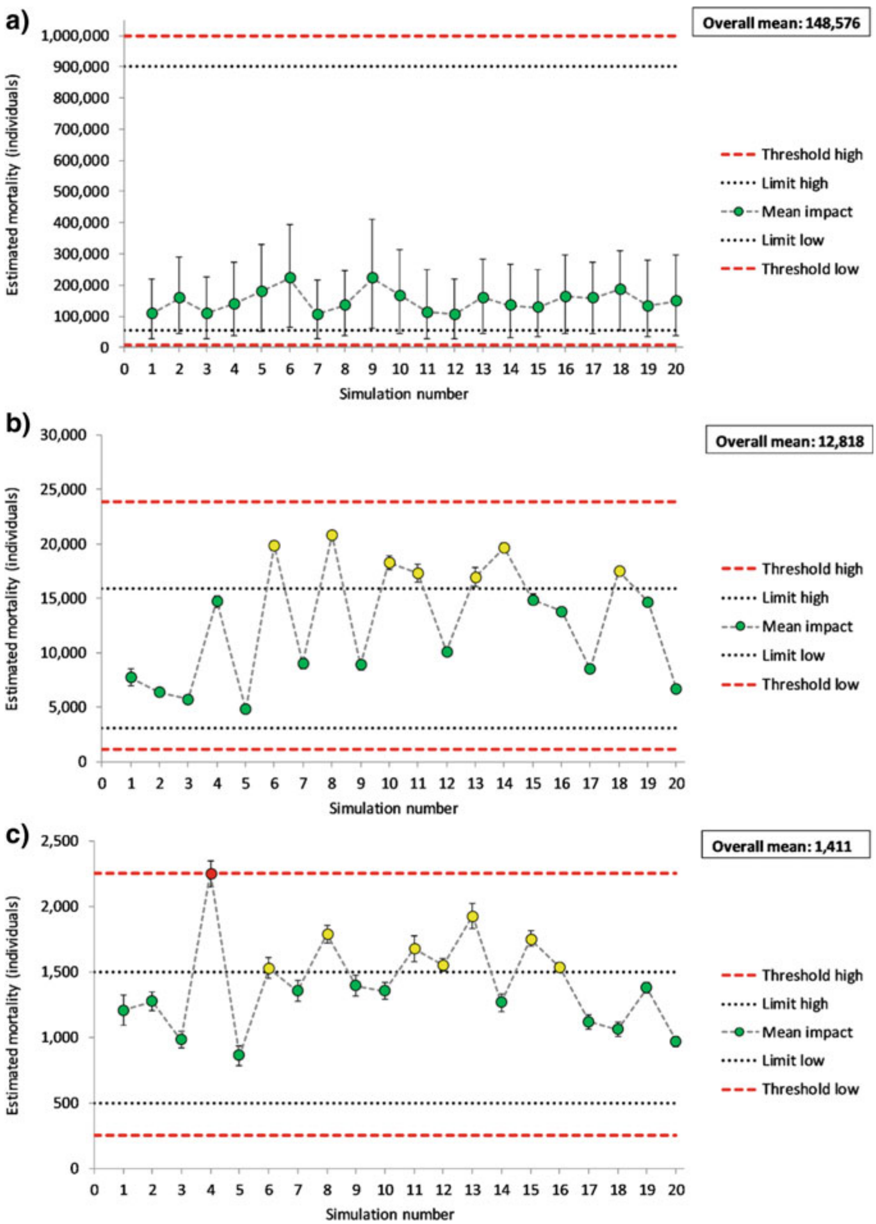

Fig. 4.11 Mortality for seabirds estimated from the 20 oil drift simulations performed in OSCAR for **a** Seabirds in the Gulf of Mexico, **b** Common murre in the Prince William Sound and **c** Pigeon guillemot in the PWS. Vertical bars show the 95% credible interval from the Monte Carlo Simulations. The larger error bars for seabirds in the Gulf of Mexico are primarily due to differences in density (D) used in the Monte Carlo Simulations (cf. Table 4.3)

on the modelled oil drift data (Table 4.7). This is mainly due to considerably longer exposure time of oil in the satellite data than in the modelled oil drift data. Compared to the performance boundaries, all simulations resulted in mortality in the "within" category.

4.2.2.2 Marine Mammals

The estimated mortality with ERA Acute for whales in the GOM was considerably underestimated compared to the field assessment and the performance boundaries. It is believed that this was primarily due to the physiological factor p_{phy} (probability of dying given contact with oil film on the sea surface thicker than 10 μm) firstly being set too low for toothed and baleen whales.

Cetaceans have in general been regarded as little vulnerable towards oil spills and the original p_{let} factor ($p_{phy} \times p_{beh}$) was 0.1%, based on early development work for the ERA Acute model and similar environmental risk analyses methods (e.g. French-McCay 2004, 2009; Østbye et al. 2003; Spikkerud et al. 2004; Spikkerud et al. 2010). Using the factors from previous work, the highest estimated ERA Acute mortality for bottlenose dolphins in the Gulf of Mexico using modelled data was 228 individuals and the highest estimate using field data was 1959 individuals, considerably underestimating the reported mortality.

During more recent development of ERA Acute, the factors were therefore re-evaluated for toothed and baleen whales (Stephansen et al. 2018) based on further scientific studies and preliminary reporting of high whale mortality from the Macondo accident (DHOS) (e.g. Deepwater Horizon Natural Resource Damage Assessment Trustees 2016). The increase in acute mortality estimated for the common bottlenose dolphin using the refined factors is illustrated in Fig. 4 12. The overall mean mortality increases from 1,128 (95% CI = 695–1,708) to 9,796 (95% CI = 6,256–14,092) individuals.

Currently recommended ERA Acute parameters are presented in Table 4.4 and are used in the results (Table 4.7), based on these calibrated vulnerability numbers for p_{phy} and $p_{beh.}$.

The mortality with the modelled oil drift data is considerably lower than the estimated mortality using the field data, with only 6 and 3% within the low and high-performance limits for the common bottlenose dolphin and the Bryde's whale, respectively (Table 4.7). The main reason for the large differences in the estimated ERA Acute mortality for satellite and model oil drift data is a considerably shorter exposure time of harmful oil in the grid cells in the modeled oil drift data (cf. Table 4.6).

For harbor seal in the PWS, the estimated mortality with ERA Acute was 195 individuals (95% CI = 28–685) resulting in an average mortality on the low side compared to the performance boundaries (Fig. 4.13a). The reasons for the large variation in the harbor seal results are partly due to relatively large uncertainty in the model parameters (cf. Table 4.4) and also possibly due to a scattered distribution in the resource dataset. The estimated mortality of or sea otters in PWS with ERA Acute

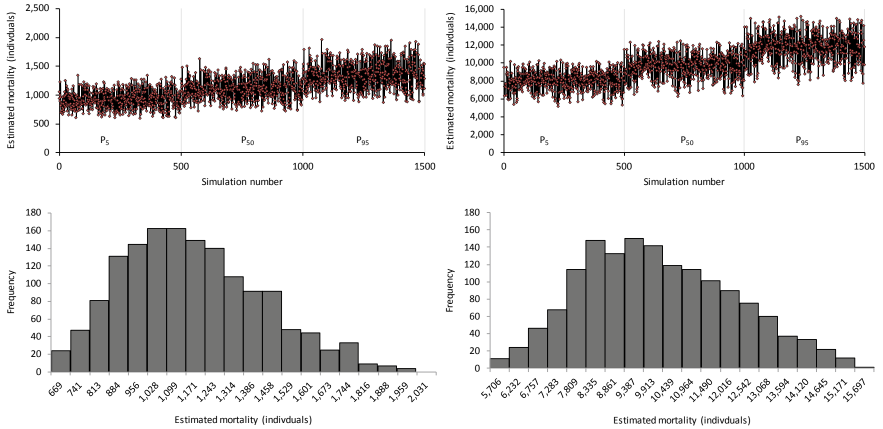

Fig. 4.12 Calibration of the individual vulnerability factors (p_{phy} and p_{beh}) for toothed and baleen whales. Impact is calculated based on oil drift statistics derived from satellite data. Result from 1500 simulations using original individual vulnerability factors (left panels) and corresponding results using the new individual vulnerability factors (right panels) for all three datasets (P_5, P_{50} and P_{95})

was 2,374 individuals (95% CI = 1,205–3,997), resulting in an average mortality within the performance boundaries (Fig. 4.13b).

4.2.3 Impact in the Shoreline Compartment

The estimated length of impacted coastline by ERA Acute using modelled oil drift data is longer for shoreline fauna than for flora. The result shows a satisfactory validation for both flora and fauna, between 55 and 85% of simulations are within performance boundaries for the two cases (DNV GL, Acona 2020). Table 4.8 summarize impact results for the EVOS and DHOS cases. The validation results for EVOS are shown in Fig. 4.14 and results for DHOS in Fig. 4.15.

The mean ERA Acute impact from all simulations is located within the performance boundaries for flora and fauna for both DHOS and EVOS. The average ERA Acute impact for shoreline fauna is similar as the reported cumulative oiling from observations: 2,225 ± 659 km SD versus 2,117 km for DHOS and 423 ± 203 km SD km versus 404 km for heavy to moderate oiling for EVOS (Gundlach et al., 1991, GEO 1994, Deepwater Horizon Natural Resource Damage Assessment Trustees, 2016).

The distribution of impact along the coastline and to a large degree, the most affected shorelines types in ERA Acute, corresponds to the estimates derived from the field data (DNV GL, Acona 2020). For EVOS, the calculated average shoreline fauna impact in ERA Acute is in line with Heavy + Moderate (HM) impact values for ESI 1 (Exposed Rocky Shores), ESI 2 (Exposed Wave-cut Platforms) and ESI 7 (Exposed

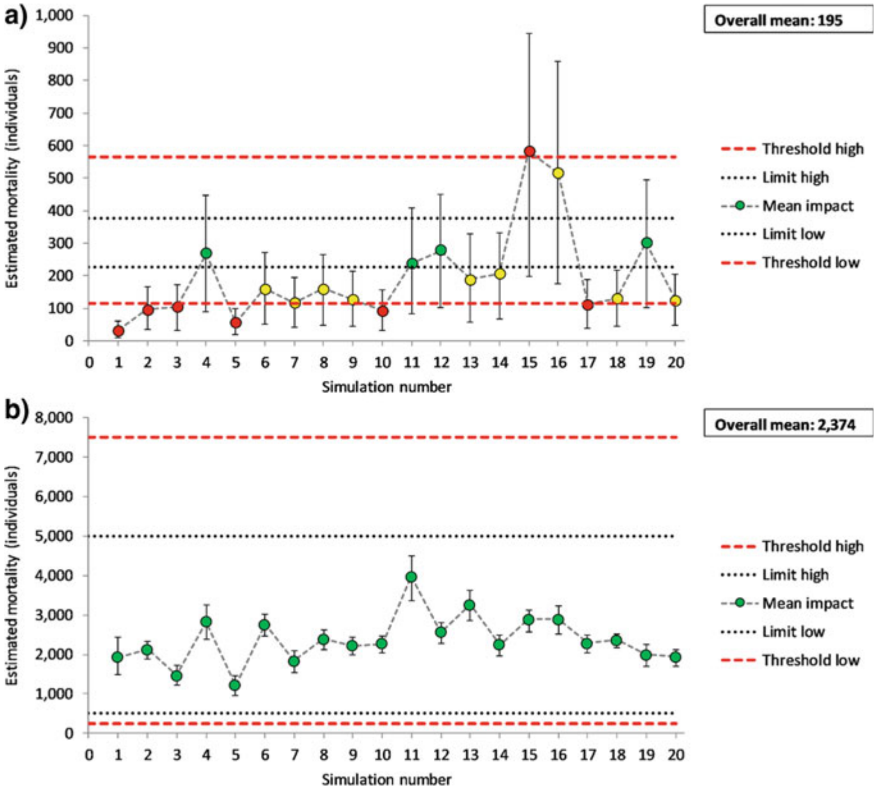

Fig. 4.13 Estimated mortality for marine mammals in the PWS from the 20 oil drift simulations performed in OSCAR shown as the mean and 95% credible intervals. **a** Harbor seal, **b** Sea otter

Tidal Flats) found in GEO (1994). For ESI 4 (Coarse-grained Sand Beaches) and ESI 9 (Sheltered Tidal Flats), ERA Acute numbers are lower than impact reported by surveys, although surveyed impact for this ESI type is limited to only a few km. For ESI 5 (Mixed Sand and Gravel Beaches), ERA Acute numbers are also too low, while they are overestimated for ESI 6 (Gravel, Cobble, Boulder Beaches). The difference might be explained by the classification in the ERA Acute VEC dataset versus the surveyed shoreline as the combined impact for these two ESI rankings are in line with surveyed numbers for Heavy + Medium + Light (HML) oiling. For ESI 8 (Sheltered Rocky Shores) and ESI 10 (Marshes), ERA Acute numbers are in between HM and HML survey numbers. For DHOS, the most affected habitat types in ERA Acute calculations are freshwater marshes, swamps (ESI 10ABC) and scrub-shrub wetlands, mangroves (ESI 10DE) and the ERA Acute calculated shoreline lengths within the five affected states was like the reported shoreline lengths of oiling in the NRDA.

A plausible reason for low impact values in some of the modelled oil trajectory simulations is that the oil drift (induced by wind and current) in these simulations is

Table 4.8 Estimated impact with ERA Acute, the performance boundaries and classification of the estimated impacts for VECs in the shoreline compartment according to the performance boundaries. The number are given as percentage of the simulations falling within the different performance boundaries rounded to nearest whole number

Case	VEC	Estimated impact with ERA acute			Performance boundaries				Classification of ERA acute				
		Mean	$P_{2.5}$[a]	$P_{97.5}$[a]	T low	L low	Within	L high	T low (%)	L low (%)	Within (%)	L high (%)	T high (%)
EVOS	Flora	423	4	144	20	39	185	340	25	10	65	0	0
	Fauna	73	62	732	86	165	788	1,446	5	15	80	0	0
DHOS	Flora	1,137	149	1,695	563	1,161	2,117	3,307	10	35	55	0	0
	Fauna	2,225	601	2,988	704	1,451	2,646	4,134	5	10	55	30	0

[a] Since only 20 simulations have been performed, $P_{2.5}$ and $P_{97.5}$ is equal to the minimum and maximum values

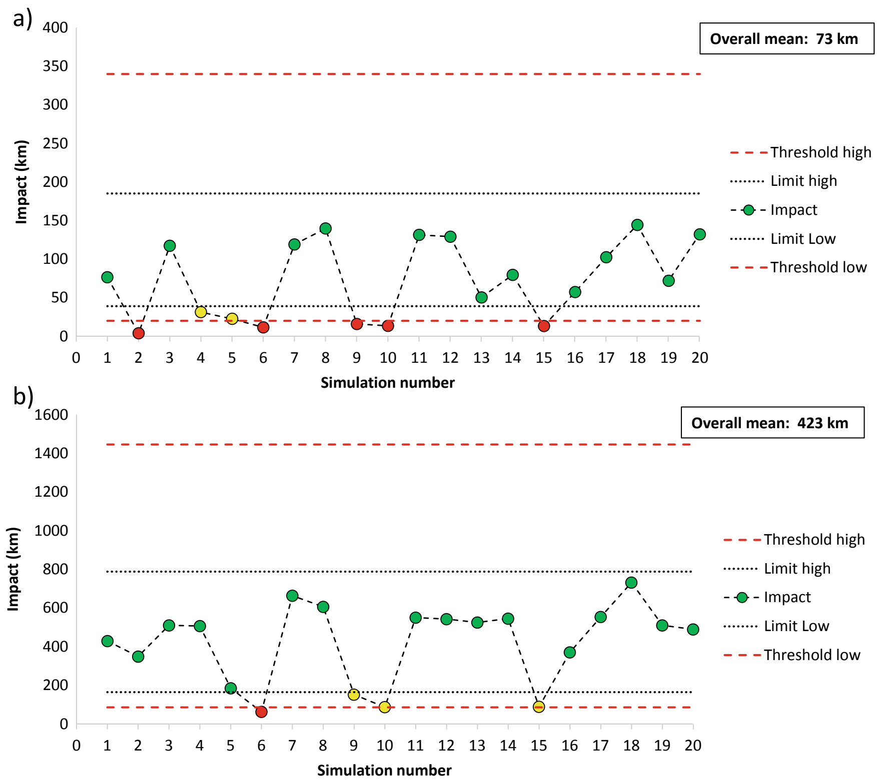

Fig. 4.14 Estimated impact calculated in ERA Acute v.1.1.0.27 for shoreline from the 20 oil drift simulations performed for the EVOS case in OSCAR. **a** Flora, **b** Fauna

not very representative for the incidents, exemplified by the impact area in simulation no. 6 and 15 for EVOS, with wind mainly from southwest during the modelled oil spill and an impact area limited to the Valdez Bay area. In DHOS, much of the oil was apparently trapped in a large stationary eddy on the northern part of the Loop Current that would not necessary be present each year and therefore is not reproduced by the oil drift simulations used as input to ERA Acute.

4.3 Discussion of the Validation

Estimating the extent of injury on natural resources has historically been a contentious, uncertain, and politically charged process. The testing and validation of the ERA Acute model is based on data that have a high degree of uncertainty. This includes oil drift data, data on distribution and abundance of VECs, historical field assessments of injury and the establishment of model parameters. A probabilistic

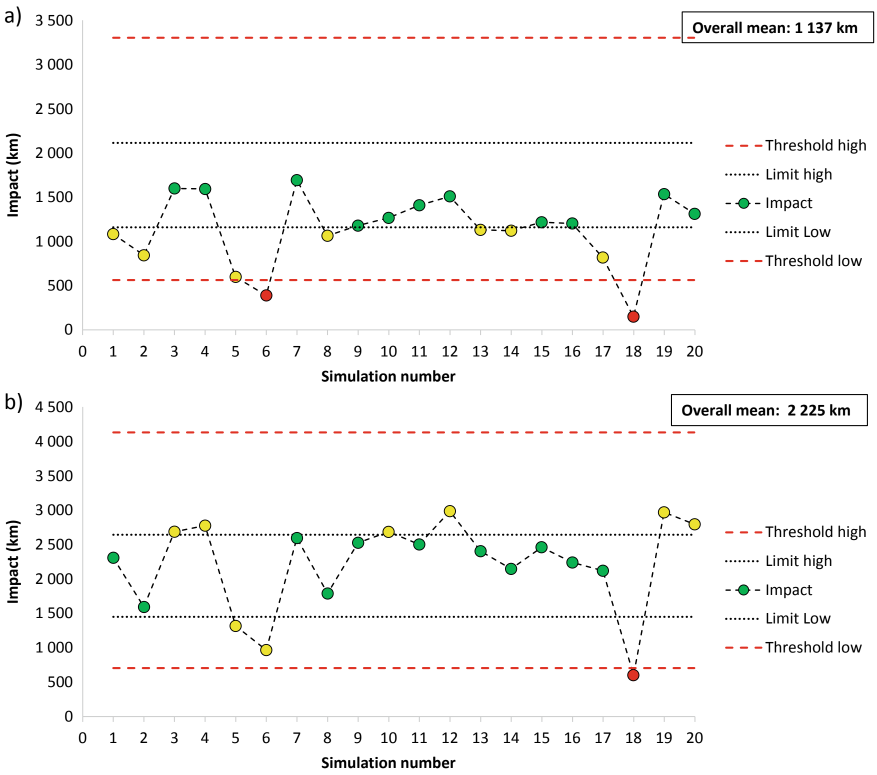

Fig. 4.15 Estimated impact calculated in ERA Acute v.1.1.0.27 for shoreline from the 20 oil drift simulations performed for the DHOS case in OSCAR. **a** Flora, **b** Fauna

approach was used to include some of this uncertainty, including VEC densities and distribution, individual vulnerability towards oil, and for model oil drift—uncertainty in the oil drift parameters.

The oil drift model used as input (OSCAR) performed reasonably well compared to field data estimates, taking into consideration uncertainty in blowout rates, reference oil types and resolution in the driver data and analysis grid. Modelled oil drift data are an important input to ERA Acute (cf. Sect. 1.5.1) and different metocean conditions constitute a significant source of variability in the prediction of spreading of oil between modelled data and actual spill incidents. Therefore, if the oil spill cases used in the validation had occurred at a different time, for example a year earlier, it is likely that the oil trajectory would be different. Much of the oil from the 2010 DHOS was apparently trapped in a large stationary eddy on the northern part of the Loop Current (cf. Wilson et al. 2010 and references therein) that would not necessary be present a different year. If, in the modelling, oil is transported out to sea instead of to the shoreline due to special weather conditions, the impact for the shoreline will be greatly underreported compared to the reported data from the incident.

An important oil drift parameter for seabirds and marine mammals is the exposure time, i.e. how long harmful oil is present in a grid cell. The oil drift model OSCAR estimated considerably shorter exposure time in the grid cells than the exposure time that what was derived from the satellite data (cf. Table 4.6). This difference is the main explanation for the relatively large difference in estimated seabird and marine mammal mortality using modelled oil drift data and oil drift data derived from satellite data in Table 4.7.

The modelled oil drift used as input to the validation study does not include oil spill response. The effect of the oil spill response on the field-estimated impact for the two incidents is not known but it is reasonable to assume that the oil spill response measures implemented during the DHOS reduced the mortality and impacted shoreline area significantly. French-McCay et al. (2018) and Bock et al. (2018) demonstrated that surface oil mass, volume and area were significantly reduced by mechanical recovery, in-situ burning, surface and subsea injection dispersant, and that the relative risks to shoreline-, surface wildlife- and most aquatic life VECs were reduced for a hypothetical deep-water oil well blowout in the Gulf of Mexico. In simulations where shoreline oiling occurred, oil spill response also resulted in less volume ashore and shorter length of shoreline affected. Including oil spill response in the OSCAR model, both offshore and in coastal areas, would have reduced ERA Acute calculated impact on shoreline habitats.

Adequately documenting tests of risk assessment models requires explicit performance criteria against which the model performance is compared (cf. Kirchner et al. 1996; Rykiel 1996). In this study we defined performance criteria based on injury estimates from incident damage assessments, as well as peer reviewed literature, from two oil spill cases. This approach was valuable for evaluating the impact estimated by ERA Acute and also for comparing the performance of two alternative impact functions for the surface compartment (cf. Sect. 3.4.1). However, the performance must be interpreted relative to the width of the boundaries. For instance, the large uncertainty in injury estimates for seabirds after the DHOS incident increases the likelihood of obtaining a high-performance score. The estimated average loss of approximately 150,000 seabirds by ERA Acute was within, but slightly low compared to the performance boundaries. The studies by Haney et al. (2014a, b) was criticized by Sackmann et al. (2015) who suggested that an underestimation of carcass transport probability to shorelines was leading to overestimation of bird deaths by an order of magnitude; a comment which was refuted in a response letter from Haney et al. (2015) (see also Beyer et al. 2016). When compared only against the injury estimates from the DHOS NRDA process, the estimated impact by ERA Acute is somewhat high (conservative), for impacts estimated using both modeled oil drift data and oil drift data derived from satellites.

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Chapter 5
Handling Uncertainty and Sensitivity of ERA Acute Towards Input Parameters

Abstract Uncertainty evaluation and sensitivity testing of the functions and parameters used in ERA Acute serve two functions. ERA Acute is a deterministic model which is sensitive to the range of values used for the parameters. Parameters have inherent uncertainties as to what their true values are, and functions may have varying strength of knowledge. The individual functions were tested with respect to their sensitivity towards variation of the parameter values using both deterministic and stochastic testing. Based on the testing, an uncertainty scoring system was used to identify and prioritize the most important parameters for reducing uncertainty. Recommendations for handling the uncertainty and securing comparability in spite of uncertainty were set up as a conclusion of the studies.

Keywords Uncertainty testing · Uncertainty handling · Sensitivity testing · Parameter sensitivity scoring · Spearman correlation coefficient analysis · Partial Rank Correlation Coefficient analysis

5.1 Sensitivity Testing and Uncertainty Handling

Every model has some inherent uncertainty. A model is a simplified mathematical description which in a quote often accredited to Albert Einstein should be "as simple as possible, but no simpler". Both the simplifications and the detailing of sub-models and equations carry with them uncertainties.

ERA Acute is a *deterministic model* where the structure of the functions and their calculation sequences reflect how we believe that oil spills may harm the VECs in the different compartments. The output of a deterministic model is completely determined by the input parameters and structure of the model. A *stochastic model* on the other hand, has inherent randomness in the model structure and will not produce the same result, even given the same parameter value (Helton et al. 2006; Marino et al. 2008).

The *functions* are mathematical descriptions of how we understand that the impact and restoration will occur, and therefore also subject to *uncertainty* about the model framework and its scientific soundness (see e.g. Gaber et al. 2009). If our assumptions

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of the mechanisms of action are uncertain, this reflects on uncertainty. As model complexity increases, the uncertainty tied to the model framework is reduced, but a more complex model uses more parameters and the data uncertainty increases (Gaber et al. 2009). For ERA Acute there are uncertainties of the model that belong to both the structure (model uncertainty) and the numerical parameters used (epistemic uncertainties).

On the condition that the functions and calculation sequences in the model are correct, if the input is not changed, the model output stays the same. In this case, uncertainty in the model output is solely affected by variation in the input parameter. This is called *Epistemic*, or reducible uncertainty (Helton et al. 2006), related to lack of knowledge of the true value of a constant parameter (Marino et al. 2008).

For the individual *parameters* used in a model it is important to distinguish clearly between:

Variability: How spread out or clustered a data set is, e.g. the (natural) variation in the measured values found in nature and
Uncertainty—The lack of certainty or knowledge about what the value of the parameter/data truly is. Such data uncertainty is specific to the individual parameter. As mentioned above, a more complex model uses more parameters and data uncertainty therefore increases (Gaber et al. 2009). ERA Acute uses many parameters.
Sensitivity Analysis (SA) tells us how the model's response can be apportioned to changes in model inputs. It is algorithm specific. For models with a high number of parameters, sensitivity analyses are useful to rank the relative importance of the factors and processes involved (Saltelli 2004).

ERA Acute is a new method and testing the sensitivity of the model to variation in the input parameters is an important part of uncertainty handling, with the goal of ensuring that ERA Acute does not under-estimate environmental risk. All data sets and parameter values have inherent uncertainties and a model consisting of a series of calculations will need some method of handling uncertainty. In the process of developing ERA Acute, the following activities were carried out:

1. Sensitivity testing of the risk functions to the variation in input parameters
2. A pilot study to score the parameters and propose feasible uncertainty handling

The functions of ERA Acute are built so that individual parameters representing biological or environmental characteristics can be improved as knowledge increases, thereby reducing uncertainty by a continuous improvement process. Sensitivity testing provides knowledge of which of the parameters that contribute most to the final endpoint values, and therefore the testing provides information on which parameters that would be most important to improve by further research if they have high uncertainty.

ERA Acute covers four compartments and uses a large number of functions. The input parameters (values and datasets) that are used are based on knowledge from few and highly diverse incidents. Validating the results of the method and applying the results with an acceptable level of (un)certainty is therefore challenging (see

Chap. 4 “Testing and Validating Against Historic Spills”). In such a case of applying a complex model and multitude of uncertain parameters, it is important to realize and accept that we do not know the “true risk” as a number as such but need to ensure that the model does not underestimate the risk and can be used to compare risks.

5.2 Methods Used in Sensitivity Testing

To test the sensitivity of the calculations towards numerical variation in the input parameters both deterministic and stochastic tests were carried out.

5.2.1 Deterministic Testing

In the deterministic testing, the impact calculations, lag- and restoration calculations within the model and its sub-models were tested by breaking them into the individual functions. By holding the other parameters constant, the input parameters were varied one by one and the resulting endpoints calculated. The results are available as graphs. The reader is encouraged to read the full reports with method description and results in: Bjørgesæter and Damsgaard-Jensen (2018) and Stephansen and Bjørgesæter (2017).

These simpler deterministic tests holding one parameter fixed at a time (One-At A-Time tests, OAT) are useful to study the direct output of varying single parameters, and thus get better acquainted with the results of the individual calculations. However, these deterministic tests are unsuitable for handling the many dimensions of variation of the input parameters, for which the global stochastic sensitivity methods are used (Marino et al. 2008).

The range in parameter values found in the literature studies during methodology development was used to define the range between the minimum and maximum values but these ranges were not used to limit the sensitivity analyses performed in the next step (see the references in the methodology development, Chap. 3 and references to Tables A.1, A.2 and A.3 in Supplementary Information 1).

A deterministic approach requires few simulations and is therefore 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; 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 therefore not possible with deterministic testing, and it is difficult to identify and rank the input parameter in terms of importance on the model output.

5.2.2 Stochastic Testing

The sub-models within ERA Acute are deterministic. To perform stochastic sensitivity testing, these models were made stochastic by using repeated random sampling (Monte Carlo (MC)) methods (Marino et al. 2008): Instead of changing the values one by one as in deterministic testing, they are assigned to a (a priori assumed) probability distribution. Configurations of model input values are then drawn randomly from the probability 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). Note that stochastic analyses are sensitive to the choice of probability distribution used (e.g. Marino et al. 2008).

The result is a matrix with *n* values for each input parameter with corresponding values for the model output (model predictions, results or endpoint) (Fig. 5.1). This matrix is the input to the uncertainty and sensitivity analysis, which is performed directly on the matrix. The sensitivity analyses were carried out using the Sampling and Sensitivity Analysis Tool for Computational Modelling (SaSat) (Hoare et al. 2008a, b). For the sensitivity analysis, Pearson and Spearman correlation coefficient, Partial Rank Correlation Coefficient (PRCC) analysis and Factor Prioritization by Reduction of Variance (FPRV) were carried out (see e.g. Saltelli et al. 2000; Marino et al. 2008). Combined, these methods can rank and quantify the most important

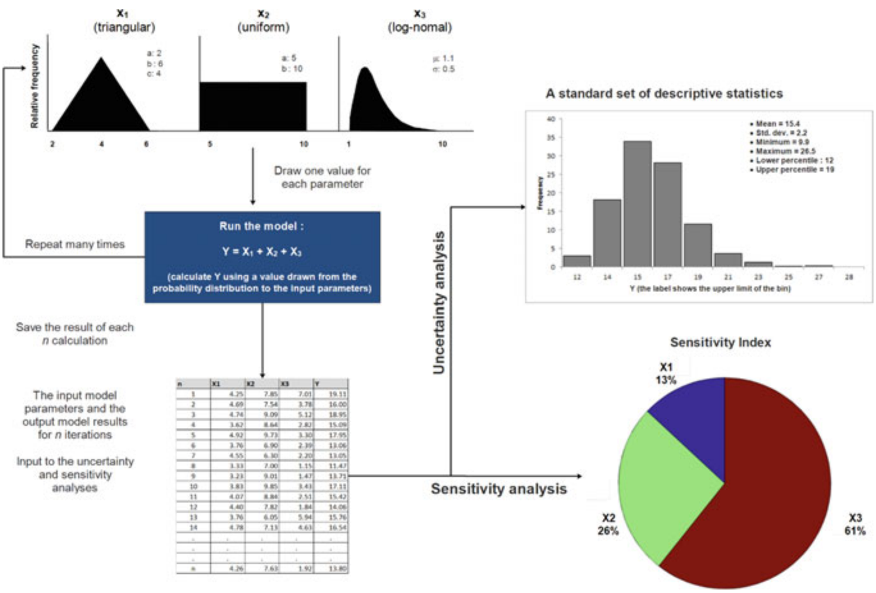

Fig. 5.1 Illustration of stochastic uncertainty and sensitivity analyses. The ERA Acute model calculations are performed in the blue box. The uncertainty analyses are performed in Excel and sensitivity analyses are performed with the MATLAB toolbox sampling and sensitivity analysis tool for computational modelling (SaSAT)

input parameters to ERA Acute. Where calculations were carried out in succession, combined formulas were used. PRCC allows independent effects of each parameter to be determined, even when the parameters are correlated. The goal is to determine which factor, once fixed to its true value by additional research, on average leads to the greatest reduction in the variance of an output. The interpretation of PRCCs assumes a monotonic relationship (relationship or function which preserves a given trend) between parameters (Marino et al. 2008). This is the case for all the (sub-) 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, monotonic relationships (Marino et al. 2008).

The result is a sensitivity index for each input parameter to the formula, which is the *fraction of the variation in the output value that can be ascribed to the different parameters. Note that this is given the uncertainty defined by the range of natural variation (results based on literature search) and the weight of each value given by the distribution (uniform—equal weight).* If a different distribution for the initial random drawing of values had been used, the result would have been different. However, given the nature of the parameters, a uniform distribution was assumed.

The use of these statistical methods in the ERA Acute sensitivity testing is described in further detail in the project reports by Bjørgesæter and Damsgaard-Jensen (2018) and Stephansen and Bjørgesæter (2017).

Impact and restoration functions were tested for each compartment and for each relevant VEC-group within the compartment having different parameter values and/or functions.

The results from the Spearman correlation coefficient analysis are presented in the test reports by Bjørgesæter and Damsgaard-Jensen (2018) for surface, water column and shoreline compartments and Stephansen and Bjørgesæter (2017) for the seafloor compartment.

5.2.3 Example from Surface Compartment

For the deterministic testing, all parameter values used for the wildlife groups are available in the test report (Bjørgesæter and Damsgaard-Jensen 2018), as well as figures showing the results for each of the tested parameters. As part of the testing it was determined that the equation which includes the exposure time (N-let2) (Sect. 3.3.1) performs best according to the impact estimated from various field estimates.

The individual factors comprising p_{let} for the surface; $p_{beh} \times p_{phy}$ were set up with values for high, medium and low estimates of the values for each of the 13 wildlife groups. The assumption behind choice of probability distribution for the stochastic drawing of values plays an important role as described in Sect. 5.2.2.

P-values and ranking according to importance from the Spearman correlation coefficient analysis for the surface compartment are presented for the parameters used in the initial impact calculation in Fig. 5.2. If the p-value (probability of type 1

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

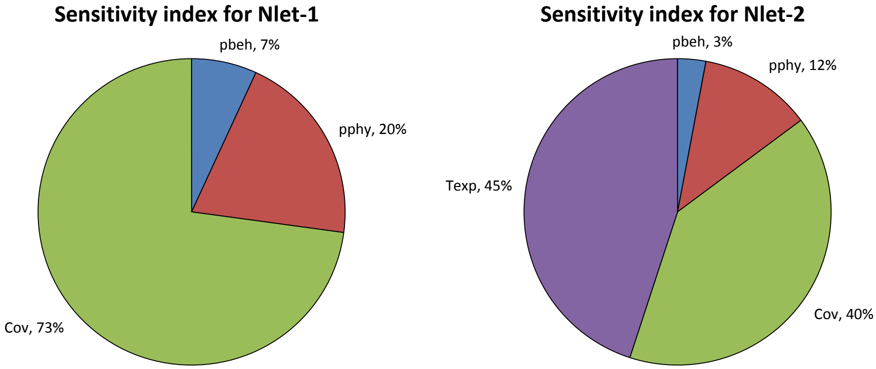

Fig. 5.2 Example of sensitivity testing: result for the sensitivity analysis of Nlet-1 and Nlet-2 for the following random variables: p_{beh}, p_{hy}, coverage (Cov) and exposure time (Texp). The relative abundance is held constant at 1

error) is below 0.05 this means that the result is statistically significant within a 95% confidence limit. The p-values were in this case $\ll$0.001. The pie diagram shows the sensitivity index from the FPRV.

The population loss is more sensitive to the variation in the oil drift impact parameters than to the variation in the two model parameters. This is also the case for the impact calculations in the other compartments. In the example from the surface compartment, the oil coverage in the grid cell is ranked as the most important variable for Nlet-1 (equation without exposure time) and as much as 73% of the total variance observed in Nlet-1 in Fig. 5.2 can be attributed to this parameter. Therefore, although all parameters are initially equally important, coverage and Texp (the latter for Nlet-2) are the most important parameters. Both values have inherent uncertainty from input parameters' and model soundness uncertainty of the oil drift simulation model. Logically, since coverage and exposure time represent the spreading and degradation of oil and the results are reported for cells at different distances from the spill and for a multitude of simulations representing very different weather conditions, it is natural that there is a large variation in the values. An inherent property of these tests is that if a tested parameter has a high variability it also becomes more important.

5.3 Uncertainty Scoring of the Parameters

A feasible way of handling uncertainty in ERA acute is necessary, using the results from the project development and testing whilst recognizing that many parameter values may need further refinement in the first years of use. A self-evaluation scoring system developed by DNV GL (Kruuse-Meyer 2015) was used to score the parameters and provide recommendations on the use of specific parameters. The scoring was based primarily on the results of sensitivity testing carried out using statistical and deterministic methods (Sect. 5.2) (Bjørgesæter and Damsgaard-Jensen 2018; Stephansen and Bjørgesæter 2017).

For each parameter the sensitivity-deciding elements were considered and assessed within the limits of the knowledge gained in previous project work according to:

Strength of knowledge (function where it is used): How strong is our confidence in that the risk function in which the parameter is used is a valid mathematical representation of the mechanism of impact/restoration?

Belief that the value may deviate from the average assumption: Natural variation of parameter. Do we believe that the values have a high natural tendency to vary from the base case (mean)? E.g. if a (standard deviation) (SD) is quantifiable, this can be used to assess this point.

Sensitivity of function to parameter (sensitivity index): How sensitive is the model/function to variation in the parameter?

Comments/recommendations on handling to ensure risk is not under-estimated: Recommended actions for ERA Acute use, data gathering etc.

5.3.1 Surface Compartment

The results of the scoring process based on the results of the deterministic and then stochastic testing and evaluation of surface compartment parameters are given in Table 5.1 for the impact parameters and Table 5.2 for the lag- and restoration time parameters.

Table 5.1 Summary of assessments or calculations used as basis for classification in the sea surface. Impact and impact time parameters

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
p_{beh}	**A** Moderate/weak. Due to limited data and large natural variation it is difficult to assign a specific p_{beh} value. The assumption that behavioural factors will affect p_{exp} is strong
	B Moderate
	C Moderate
	Comments/recommendations: A higher value is conservative. Each VEC have three estimates (low, intermediate, high), using high is most conservative. Alternative, use all to obtain larger credible interval
Cov	**A** Moderate/weak. The parameter depends on other parameters evaluated as Moderate/weak. The assumption that that exposed area will affect p_{exp} strong
	B High
	C Moderate
	Comments/recommendations: A higher value is conservative. Coverage is calculated by the oil drift model. Use Best Practice for oil drift simulation set-up to ensure comparable and reliable predictions of the statistic
Texp	**A** Moderate/weak. The parameter depends on other parameters evaluated as Moderate/weak. Based on stochastic result (i.e. estimated over the whole simulation period). The assumption that the exposure time will affect p_{exp} is strong
	B High
	C High
	Comments/recommendations: A higher value is conservative. Exposure time is calculated by the oil drift model. Use Best Practice input data and setup for the ODS to ensure comparable and reliable predictions
p_{phy}	**A** Moderate/weak. Due to lack of experimental data, it is difficult to assign a specific p_{phy} values. The assumption that the physiological factors will affect p_{let} is strong
	B Low/Moderate/High, depending on VEC Low for seabirds and moderate to high for marine and aquatic mammals and sea turtles
	C Moderate
	Comments/recommendations: A higher value is conservative. Each VEC have three estimates (low, intermediate, high), using high is most conservative. Alternative, use all to obtain larger credible interval

(continued)

Table 5.1 (continued)

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
Th	**A** Moderate/weak Due to lack of experimental data, it is difficult to assign specific threshold levels for lethal oil film thickness
	B Moderate
	C High
	Comments/recommendations: A threshold value, lower value is conservative. Oil thickness is calculated by the oil drift model. Use Best Practice for ODS to ensure comparable and reliable predictions. Based on present knowledge, reducing Th from 10 to 2 μm, increases the impact with a factor of approximately 2.0–2.5, depending on the distribution of the VEC and the distance to the release point
N per cell	**A** Moderate/weak Depends on the quality of the data received from the data provider. The quality of the data for the NCS is considered high
	B High
	C Moderate/high
	Comments/recommendations: Use the best available data to reduce uncertainty. Use the same data for comparable studies. The definition of a "population" is important

5.3.2 Water Column Compartment

Results of the scoring and evaluation of water column parameters are given in Table 5.3 for the impact parameters and Table 5.4 for recovery parameters.

5.3.3 Shoreline Compartment

Results of the scoring and evaluation of shoreline parameters are given in Table 5.5 for impact parameters and Table 5.6 for recovery parameters.

5.3.4 Seafloor Compartment

Results of the scoring and evaluation of seafloor parameters are given in Table 5.7 for impact parameters and Table 5.8 for recovery parameters.

Table 5.2 Summary of assessments or calculations used as basis for classification in the sea surface. Lag time and restoration time parameters

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
Nhab	**A** Moderate/weak The function includes various not well-defined or understood subtle effect other than acute mortality
	B High
	C Moderate
	Comments/recommendations: Using the function will increase the total recovery time, typically with 5–30% of the shoreline lag-times but depending on the importance of the affected shoreline habitats
SF	**A** Moderate/weak
	B High
	C Moderate
	Comments/recommendations: Use conservative value
t_lag (shoreline)	**A** Moderate/weak. Due to lack of experience data, it is challenging to assign specific lag time periods for different types of shoreline habitats
	B High
	C High/Moderate
	Comments/recommendations: Higher values are more conservative. Standard values for SF for different VECS and/or area are not derived. May use the same data as for calculating acute mortality (filtered for shoreline cells)
R	**A** Moderate/weak. The logistic discrete population model is a simplification of real-world population dynamics. Common R values are used for different species and populations as a standard (see b)
	B Moderate/high
	C High
	Comments/recommendations: Lower values are more conservative. The R values are conservative compared to the damage keys used in MIRA (using standard values for b, K and TLR). Field validation studies indicates that the model performs reasonably well, for population not inhibited by unknown extrinsic factors (using standard R, b, K and TLR values)
b	**A** Moderate/weak. The parameter determines the strength of intraspecific competition; a simplification of real-world population dynamics
	B High
	C High

(continued)

Table 5.2 (continued)

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
	Comments/recommendations: Lower values are more conservative. Used to reflect population growth in population inhibited by unknown extrinsic factors or the general status of the population ("poor", "intermediate", "good"). Use low b values to further increase the conservatism of the population model predictions
K	**A** Moderate/weak
	B High. Large fluctuations of population size above and below carrying capacity is common in nature
	C High
	Comments/recommendations: The carrying capacity of the environment (K) is the maximum population size that the environment can sustain. It is set equal to the population size before the oil spill release (100%) and is used as a reference point for when the population is considered recovered
TRL	**A** Moderate/weak Cut off to avoid $t_{res} = \infty$ in a logistical growth model
	B High
	C High/moderate for t_{res}, Moderate/low for RDF (effect varies with percentage population loss)
	Comments/recommendations: Higher values are more conservative. Can be chosen differently for higher level of conservatism. Using values above 95% may lead to unrealistic long Restoration times

5.4 Recommended Uncertainty Handling at This Point in Model Development

Ideally, it should be one of the goals to arrive at a quantified estimate of the degree of accuracy of the endpoints of impact and restoration modelling. However, to arrive at this, more and continuous improvement is needed. Instead, general recommendations are given for ensuring comparability and reducing variability:

- Use the *conservative* values included in the method reports and current guideline
- Use *quality* data sources from acclaimed institutions
- Seek *improved* data for the factors to which the model is most sensitive to where possible
- Use *standardised* data sets and input parameters for analyses that are to be compared.

Table 5.3 Summary of assessments or calculations used as basis for classification in the water column. Impact parameters

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
Plet, THC Extracted from SSD-curve	**A** Strong
	B Moderate. SSD-curve based on LC50 for 24 species
	C High
	Comments/recommendations: Estimated from THC and a log-normal SSD curve with standard deviation of 0.32. A lower standard deviation is conservative (shift the SSD curve to higher THC values)
THC	**A** Moderate/weak. Vertical maxima, THC includes numerous components with varying toxicity
	B High
	C High
	Comments/recommendations: THC is calculated by the oil drift model. Use Best Practice for ODS set-up to ensure comparable results. Use a concentration grid (with many layers) that cover the same water column where the fish egg/larva are distributed
Frackilled	**A** Strong. Estimated in OSCAR during the ODS
	B Moderate
	C High/Moderate/Low (depending on setting)
	Comments/recommendations: Estimated by OSCAR during the ODS (potential acute mortality in a cell). Standard deviation (SD) of the SSD and the species sensitivity may be adjusted before one run the ODS. The species sensitivity is a safety factor. The OSCAR database LC50 values will be divided by this factor, accounting for more (factor >1) or less (factor <1) sensitive fish larva/egg
N per cell	**A** Strong. Depends on the quality of the data received from the data provider. Compared to e.g. birds the distribution is to a large degree dependent on sea currents
	B Moderate
	C Moderate/high
	Comments/recommendations: Use the best available data to reduce uncertainty and increase the quality of the predictions. Use the same data for comparable studies

Table 5.4 Summary of assessments or calculations used as basis for classification in the water column. Recovery parameters

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
CritDens (%)	**A** Moderate/weak
	B High
	C High (threshold level between two methods with different conservatism)
	Comments/recommendations Higher values are more conservative. Expresses the threshold for when a direct relationship is modelled between larval mortality and recruitment reduction
CritOilMort (%)	**A** Moderate/weak
	B High
	C High (threshold level between two methods with different conservatism)
	Comments/recommendations Lower values are more conservative. Expresses the threshold mortality of eggs and larvae for which a proportionate relationship is calculated between killed larvae and reduced recruitment
Annual natural mortality of immatures (%)	**A** Moderate/weak
	B Moderate/high
	C Not tested
	Comments/recommendations
Annual natural mortality of matures (%)	**A** Moderate/weak
	B Moderate/high
	C Not tested
	Comments/recommendations
Age at recruitment (year)	**A** Moderate/weak
	B Low/moderate
	C Not tested
	Comments/recommendations
Age at first spawning (year)	**A** Moderate/weak
	B Low
	C Not tested
	Comments/recommendations

(continued)

Table 5.4 (continued)

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
Maximum age (year)	**A** Moderate/weak
	B Low
	C Not tested
	Comments/recommendations

Table 5.5 Summary of assessments or calculations used as basis for classification in the shoreline. Impact parameters

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
Tidal range (m)	**A** Moderate/low
	B Moderate/low (Coastal tidal ranges vary considerably depending on the volume of water adjacent to the coast, and the geography of the basin. Tidal range also varies depending on the locations of the moon and sun)
	C Low
	Comments/recommendations: Lower values are more conservative. The parameter is cell specific and is used to estimate oil thickness
Slope (°)	**A** Moderate/low
	B High/moderate (the slope of the beach may vary considerable with a shoreline habitat type)
	C High
	Comments/recommendations: Higher values are more conservative. The parameter is ESI specific and is used to estimate oil thickness
OHC	**A** Moderate/low
	B High/moderate (the distribution of oil along the shoreline will also depend on factors such as current, wind, geography, that are difficult to accurately estimate outside the oil drift model)

(continued)

Table 5.5 (continued)

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
	C Moderate/high
	Comments/recommendations: Higher values are more conservative. The parameter is ESI specific and is used to distribute the stranded oil mass along the shoreline in a cell. Higher value means that more of the stranded mass is allocated to the shoreline habitat
Patchiness factor	**A** Moderate/low. Due to lack of experience data, it is challenging to assign a specific patchiness factor
	B High. Patchiness of oil may range from 1 to 100%
	C High
	Comments/recommendations: Lower values are more conservative. Fixed look-up values
Th	**A** Moderate/low. It is difficult to assign a specific threshold level for lethal oil film thickness for invertebrates and vegetation
	B Moderate
	C High (threshold value)
	Comments/recommendations: Higher values are more conservative. Threshold level for impact, 0.1 mm for invertebrates and 1.0 mm for wetland vegetation
Stranded mass (ton)	**A** Moderate/low. Basis for calculating film thickness
	B High
	C High/moderate (proportional)
	Comments/recommendations: Higher values are more conservative Stranded mass is calculated by the oil drift model. Use Best Practice for ODS to ensure comparable and reliable predictions
Shoreline length (km)	**A** Strong. Depends on the quality of the data received from the data provider
	B Low/moderate
	C High (proportional)
	Comments/recommendations: Use the best available data to reduce uncertainty and increase the quality of the predictions. Use the same data for comparable studies
Shoreline rankings	**A** Strong. Depends on the quality of the data received from the data provider
	B Moderate
	C High for recovery (lag-time and restitution)
	Comments/recommendations: ESI rankings; 1 least sensitive, 10 most sensitive

Table 5.6 Summary of assessments or calculations used as basis for classification in the shoreline. Lag-time and recovery parameters

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
Lag-time	**A** Moderate/low. Due to lack of experience data, it is challenging to assign specific lag-time periods for shorelines
	B High/moderate. Variable and to a large degree depending on weather conditions
	C High
	Comments/recommendations: Fixed look-up values
Recovery	**A** Moderate/low. Due to lack of experience data, it is challenging to assign specific restitution time periods for shorelines
	B High Variable depending on invertebrate and flora communities
	C High
	Comments/recommendations: Fixed look-up values

Table 5.7 Summary of assessments or calculations used as basis for classification in the seafloor. Impact parameters

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (Natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)		
Mixing depth	**A** Strong/moderate. Knowledge of what constitutes the bioturbation depth is relatively strong		
	B High uncertainty		**C** 40.0% high
	Comments/recommendations: A lower value is conservative, lower values are default for all substrates based on size of typical burrowing fauna in substrate. High natural variation: Either look for local real values or use conservative value		
Dry density	**A** Strong	**B** Low	**C** 0.5% low
	Comments/recommendations: Schultz and Zabel (2006) give general values. Low sensitivity, use defaults		
Water Content	**A** Strong	**B** Low/moderate	**C** 2.7% low
	Comments/recommendations: Use lower values as conservative		
Total org. Carbon	**A** Strong (EqP accepted methodology)		
	B High		**C** 54.9% high
	Comments/recommendations: Use conservative (lower) values. Lower values lead to higher toxicity and shorter restoration times (Higher TOC sequesters THC in sed.)		

(continued)

Table 5.7 (continued)

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (Natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)	
KOW	**A** Strong (EqP accepted methodology)	
	B Moderate	**C** 1.8% low
	Comments/recommendations: Value calculated based on typical components with affinity to organic carbon in sediment. Use as implemented, can be changed, but has low impact on result	
Plet (SSD-curve used)	**A** Strong	
	B High to low depending on species sensitivity	
	C High	
	Comments/recommendations: Conservativity implemented by the curve being conservatively extrapolated from the LD5-value from a large and quality-assessed set of data (Nilsen et al. 2006). SSD curves are accepted methodology and inherent safety factor used and can be increased for sensitive species	
THCsed (used as input from OSCAR)	**A** Strong knowledge of place in ERA Acute function	
	B Is calculated by the OD model. SD is low within calculations in same model, may vary a lot between inputs from different models	
	C High (proportional)	
	Comments/recommendations: THCsed calculations in OSCAR do currently not take into consideration the grain size or TOC-content of the substrate (these factors are used by ERA Acute to modify the exposure in the initial calculations. No conservativity is included, but the other factors are chosen conservatively. The calculations in sediment in OSCAR are undergoing improvements, e.g. by possible inclusion of marine snow	
THC (WC)	**A** Strong knowledge of place in SSD-curve	
	B High uncertainty and the THC concentration is a time-averaged concentration	
	C High (proportional)	
	Comments/recommendations: The concentration is calculated as a time-averaged THC-value. This is a weakness in the approach. Use of dynamic time-steps output options (e.g. proposed in the ERA Acute Dynamic Risk Assessment incl. MIZ-proposal) could improve this. Conservativity is applied as we currently do not have available from OSCAR the THC-conc. in the lower WC, and therefore use the upper layers as for compartment WC. This is conservative	
N	**A** High strength of knowledge	
	B Moderate	**C** High (proportional)
	Comments/recommendations: Use quality data on presence or habitat area/fractions. Sampling of benthic species may lead to uncertainties, use data that are based on accepted sampling methods by accredited data sources	

Table 5.8 Summary of assessments or calculations used as basis for classification in the seafloor. Lag-time and restoration parameters

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (Natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
$C_{threshold,sed}$	**A** Moderate strength of knowledge of function
	B High
	C High
	Comments/recommendations: Concentration of THC at which effects on faunal communities in sediment cannot be detected in monitoring studies (Renaud et al. 2008). Species may be more sensitive or less
$C_{benchmark\text{-}max,sed}$	**A** Moderate strength of knowledge of function
	B High
	C High
	Comments/recommendations: Value representing the maximum value at equilibrium. Based on data from the MOD data base (North Sea)
20 years def value	**A** Moderate strength of knowledge of function
	B High
	C High
	Comments/recommendations: Based on MOD data from North Sea, mostly sandy bottom, few sites have data on restoration times after use of oil-based drilling muds
SF	**A** Moderate strength of knowledge of function
	B High
	C High (proportional)
	Comments/recommendations: Theoretical calculation of the leaching of THC from organic carbon, simplified approach based on physical-chemical properties of THC bound to organic carbon in sediments (resuspension and redistribution may vary between substrates and is not included). The SF was introduced to the function to modify the calculated restoration time
t_{lag} (hard)	**A** Fixed value
	B High
	C High
	Comments/recommendations: Very little research available after oil spills affecting deep sea corals. Comparable incident DHOS not yet restored

(continued)

Table 5.8 (continued)

Main parameter	A: Strength of knowledge (*function* where it is used) B: Belief that the value may deviate from the average assumption (Natural variation of parameter) C: Sensitivity of function to parameter (sensitivity index)
t_{res} (Hard)	**A** Fixed value
	B High
	C High
	Comments/recommendations: Very little research available after oil spills affecting deep sea corals. Comparable incident DHOS not yet restored

Within a region, e.g. a country for which assessments should be used for applications to the authorities, this means that the industry should work together to test new values, gain common knowledge and understanding of the sensitivities as well as use common data sets. Calibration of the parameter values should be carried out after testing and documentation of the effects, and results discussed between scientists from both industry, consultancies, authorities and research institutions. The goal is *continuous, but structured and synchronised improvement.* A summary of the recommendations for each of the most important parameters is given for each compartment in Tables 5.9 and 5.10.

Table 5.9 Prioritised parameters with a potential for improvement or parameters that have a high impact on the result, with recommended action for uncertainty handling (surface compartment parameters)

Parameter	Recommendation for improvement
Cov	Use oil drift model that uses a state-of-the art calculation of oil coverage above the threshold on the surface with best practice settings
Texp	Use oil drift model that uses a state-of-the art calculation of the time with oil above the threshold level on the surface, with best practice settings. Setting a minimum exposure time could be beneficial to not underestimate impact
R	Net *fundamental* growth rate is based on demographic data (age at first and last reproduction, annual birth rate, pre-reproductive and adult survival probability) and literature review of different species and categorised into seven major groups. Updating knowledge and adding more data would increase certainty of the R values
TLR	Current restoration function is asymptotic, the threshold level for when the population is recovered is highly sensitive
b	The *realised* growth rate can be inherently different for different populations (or colonies or groups) of the same species when recovery is inhibited by known or unknown extrinsic factors (high predation, hunting, food shortage, disease etc.). Updating the knowledge and adjusting the factor (b) for these “populations” would improve certainty. A practical solution for standard environmental risk analyses is to apply three values for the b factor as a measure of the “general health” of the population/colony (“good”, “medium” and “poor”). The same effect may be obtained by adjusting the net fundamental growth rate R

Table 5.10 Prioritised parameters with a potential for improvement or parameters that have a high impact on the result, with recommended action for uncertainty handling (shoreline, water column and seafloor compartment parameters)

Parameter	Recommendation for improvement
Shoreline	
Mass	High importance but proportional. Use oil drift model that uses a state-of-the art calculation of beached mass, with best practice settings
Patchiness factor	The value is a fixed value based on research. Lack of data available, could be improved with more research. Value in 2020 is 0.30 based on calibration
Slope	ESI-specific. Use best practice ESI dataset
Lag-time/Recovery time	Fixed values that could be improved with more research
Water column	
CM	Use a best practice recommendation for setting the Critical Mortality value for when the gate model is used
Seafloor	
TOC	Total organic content in the soft substrate determines the partitioning between oil adhered to the substrate and oil that is bioavailable in interstitial or gut water, and thereby the exposure and lethality. The value may vary a lot regionally depending on the background concentration of organic matter and substrate type. Monitoring studies could include this parameter for regionally/nationally improved quality of the substrate data
BDepth	Mixing depth scales the result proportionally and varies with the type of burrowing fauna. The variation in results from different studies is high. Monitoring studies could include this parameter for regionally/nationally improved quality of the substrate data
WC oil concentration	Exposure through water column determines much of the impact for all feeding modes that have exposure though water column. Best result if using oil drift modelling that provides a separate water column concentration from the bottom layer
THCsed	Start-value of oil concentration in the soft substrates. Use an oil drift model that provides a state-of-the-art calculation of oil in the sediment corrected for the substrate type (TOC-content)

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Supplementary Information 1

A.1 Surface Compartment Parameter Values

See Tables A.1, A.2 and A.3.

Table A.1 Generic individual behavioral factors (p_{beh}) table

Wildlife group			Thickness (µm)	p_{beh}		
No	Name			Low (%)	Intermediate (%)	High (%)
1	WG1	Pelagic diving seabirds	2	78	88	98
2	WG2	Pelagic surface foraging seabirds	2	45	51	56
3	WG3	Coastal diving seabirds	2	67	76	84
4	WG4	Coastal surface feeding seabirds	2	32	36	40
5	WG5	Wetland surface feeding seabirds	2	48	54	60
6	WG6	Wading seabirds	2	48	54	60
7	WG7	Baleen whales	10	70	79	88
8	WG8	Toothed whale	10	80	90	100
9	WG9	True seals, walrus and sea lions	10	84	88	93
10	WG10	Fur seals	10	63	78	93
11	WG11	Sea cows	10	95	98	100
12	WG12	Aquatic mammals	10	79	88	97
13	WG13	Sea turtles	10	95	99	100

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Table A.2 Generic individual physiological factors (p $_{beh}$) table

Wildlife group			Thickness (µm)	p_{phy}		
No	Name			Low (%)	Intermediate (%)	High (%)
1	WG1	Pelagic diving seabirds	2	80	90	100
2	WG2	Pelagic surface foraging seabirds	2	80	90	100
3	WG3	Coastal diving seabirds	2	80	90	100
4	WG4	Coastal surface feeding seabirds	2	80	90	100
5	WG5	Wetland surface feeding seabirds	2	80	90	100
6	WG6	Wading seabirds	2	80	90	100
7	WG7	Baleen whales	10	2.5	5.0	7.5
8	WG8	Toothed whale	10	4.0	8.0	12
9	WG9	True seals, walrus and sea lions	10	5.0	10	15
10	WG10	Fur seals	10	50	72	93
11	WG11	Sea cows	10	4	8	12
12	WG12	Aquatic mammals	10	50	72	93
13	WG13	Sea turtles	10	2.0	4.0	6.0

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A.2.1 Oil Film Thickness

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Table A.3 Generic fundamental net reproductive rates (R) table

Wildlife group		Typical species	*R*
Name			
WG1	Albatross and skuas	Albatross (Southern royal, Grey-headed Antipodean, Northern royal), skua (brown, great, subantarctic), Northern fulmar	1.05
WG2	Auks, petrels and shearwaters	Auks (razorbill, common guillemot, Atlantic puffin), petrels (black, white-chinned, Chatham), shearwaters (Bullers, flesh-footed), Black-legged kittiwake	1.10
WG3	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)	1.15
WG4	Cormorants, shags, divers, ducks and gooses	Cormorant (great), shags (European, Campbell Island, spotted, Auckland Island), divers (red throated), ducks (common eider, common scooter) and goose (barnacle, snow, Bewicks swan)	1.20
WG5	True seals, sea lions and fur seals, baleen whales	Grey seal, harbor seal, ringed seal, Antarctic fur seal, subantarctic fur seal, blue, humpback and southern right whales	1.13
WG6	Walrus, aquatic mammals	Walrus, polar bear, Eurasia otter, sea otters	1.06
WG7	Toothed whales, sea cows, sea turtles	Bottlenose dolphin, killer whale, harbor porpoise, Florida manatee, sea turtles	1.03

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