HELSINGIN YLIOPISTO
HELSINGFORS UNIVERSITET
UNIVERSITY OF HELSINKI

Bayesian bioeconomic prediction model for assessing oil spill impacts on a fish population – case Baltic Sea herring

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Sami Vikkula
e-mail: sami.vikkula@helsinki.fi
phone: +358400421354
Supervisors: Sakari Kuikka, Samu Mäntyniemi

HELSINGIN YLIOPISTO

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Tiivistelmä - Referat - Abstract

Öljyvahingot vesiympäristöissä ovat kauheita onnettomuuksia, joilla on sekä biologisia, että taloudellisia vaikutuksia. Näiden vaikutuksien kohteina ovat muun muassa kalapopulaatiot. Öljyonnettomuuksien vaikutuksia kalapopulaatioihin on kirjallisuudessa tutkittu paljon. Käytettyjen tutkimusmenetelmien joukosta tässä tutkielmassa keskitytään Bayes-menetelmiin.

Aiemmissa tutkimuksissa on kehitetty useita Bayes-menetelmiin perustuvia öljyvahinkojen vaikutusten arviointimalleja. Nämä mallit kuitenkin keskittyvät useimmiten menneisyydessä tapahtuneiden onnettomuuksien vaikutusten arviointiin. Kehitettyjä malleja ei ole käytetty mahdollisten tulevaisuudessa tapahtuvien onnettomuuksien vaikutusten ennustamiseen. Niissä ei myöskään ole hyödynnetty laboratoriotutkimusten avulla saatuja tuloksia vaikutusten arvioinnissa. Esimerkkejä öljyvahinkojen taloudellisia vaikutuksia arvioivista malleista on saatavilla vain vähän, eikä mikään niistä arvioi taloudellisia vaikutuksia öljyn aiheuttaman kalakannan biomassan muutoksen kautta.

Tämän tutkielman tarkoituksena on kehittää Bayes-menetelmiin perustuva bioekonominen ennustusmalli, jolla voisi ennustaa öljyvahingon vaikutuksia Itämeren pääaltaan silakkapopulaatioon, sekä näiden vaikutusten aiheuttamia taloudellisia seurauksia kalastajille. Kehitettävällä mallilla on tarkoitus ennustaa erilaisten hypoteettisten öljyvahinkojen vaikutuksia.

Tutkielman tuloksena saatiin kehitettyä ennustusmalli, jolla voi ennustaa erilaisten hypoteettisten öljyvahinkojen vaikutuksia mätimunien lisäkuolleisuuden kautta sekä Itämeren pääaltaan silakkapopulaatioon, että kalastajille aiheutuviin taloudellisiin seurauksiin. Mallia voidaan soveltaa myös muihin kalapopulaatioihin muilla alueilla. Mallissa hyödynnetään laboratoriotutkimusten tuloksia öljyvahinkojen vaikutusten arvioinnissa. Mallia voidaan käyttää sekä mahdollisten tulevaisuudessa tapahtuvien öljyvahinkojen aiheuttamien riskien arviointiin, että jo tapahtuneiden onnettomuuksien jälkeen tapahtuvaan päätöksentekoon. Lisäksi mallia voidaan käyttää menneisyydessä tapahtuneiden onnettomuuksien tuntemattomien aspektien arviointiin. Taloudellisia ennusteita voidaan käyttää muun muassa kalastajille mahdollisesti maksettavien korvausten arviointiin. Tulevaisuudessa ennustusmallia tulisi kehittää erityisesti tarkentamalla kalakannan rekrytointiin liittyviä oletuksia mahdollisimman hyvin todellisuutta vastaaviksi. Lisäksi mallissa tehtyjä oletuksia liittyen öljyn aiheuttaman lisäkuolleisuuden ja taloudellisten vaikutusten laskemiseen tulisi laajentaa.

Avainsanat – Nyckelord
Öljyvahinko, Bayes, ennustaminen, taloudellinen, kanta, rekrytointi, riskin arviointi, päätösanalyysi

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Oil spills in aquatic environments are devastating disasters with both biological and economic impacts. Fish populations are among the many subjects of these impacts. In literature, there are numerous assessments of oil spill impacts on fish populations. From all applied research methods, the focus of this thesis is on Bayesian methods.

In prior research, several Bayesian models have been developed for assessing oil spill impacts on fish populations. These models, however, have focused on the assessment of impacts from past spills. They have not been used for predicting impacts of possible future oil spills. Furthermore, the models have not utilized data from laboratory studies. Some examples can be found of models assessing economic impacts of oil spills on fish populations however, none of them assess the economic impacts that follow from decreases in biomass.

The aim of this thesis is to develop a Bayesian bioeconomic prediction model, which would be able to predict oil spill impacts on Baltic Sea main basin herring population, and the consequential economic impacts on fishermen. The idea is to predict the impacts of several hypothetical oil spill scenarios.

As a result of this thesis, a bioeconomic prediction model was developed, which can predict both biological and economic impacts of oil spills on Baltic Sea main basin herring through additional oil induced mortality of herring eggs. The model can be applied to other fish populations in other regions as well. The model utilizes laboratory studies for assessing population level impacts. The model can be used for both assessing risks of the impacts of possible future oil spills, and for decision analysis after a spill has already occurred. Furthermore, the model can be used for assessing unknown aspects of past oil spills. The economic predictions can be used, for example, to estimate the compensations that could possibly be paid to fishermen. In the future, the prediction model should be developed further, especially regarding its stock-recruitment relationship assumptions. In addition, the model's assumptions regarding the calculation of oil induced additional mortality and the economic impacts, should be expanded.

Avainsanat – Nyckelord **Öljyvahinko, Bayes, ennustaminen, taloudellinen, kanta, rekrytointi, riskin arviointi, päätösanalyysi**	
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List of important abbreviations

API (gravity) = American Petroleum Institute

BHM = Bayesian hierarchical model

BMA = Bayesian model averaging

GoF = Gulf of Finland

IMOLS = Instantaneous mortality on log scale

MAH = Monocyclic aromatic hydrocarbon

MCMC = Markov chain monte carlo

MSY = Maximum sustainable yield

OWD = Oil water dispersion

PAH = Polycyclic aromatic hydrocarbon

TAC = Total allowable catch

TPAH = Total polycyclic aromatic hydrocarbon

TPH = Total petroleum hydrocarbon

1 Introduction

1.1 Background and aim of the thesis

Oil spills in aquatic environments are devastating disasters with both biological and economic impacts. Human activities, such as offshore oil drilling and transportation of oil, expose aquatic environments to oil spill impact risks. For managing these risks, it is important to be able to assess oil spill impacts, both from the past and into the future.

Fish populations will most likely become subjects to the impacts of oil after it has been spilled into water. Effects of past oil spills on fish population abundance and dynamics have been assessed in numerous studies. (e.g., Rahikainen et al. 2017; Muradian et al. 2017; Ward et al. 2017; Lecklin et al. 2011; Langangen et al. 2017; Brown et al. 1996). The assessed past effects vary from minor to more severe. Each oil spill is unique in its characteristics including, for example, the type of spilled oil, volume of spilled oil, concentration of toxic compounds in water after a spill, and prevalent weather conditions during and after the spill (Fingas et al. 2011). Each of these characteristics influence the magnitude of the impacts of oil on the environment and fish populations.

Oil impacts on different life stages of fish have been studied extensively in laboratory studies (e.g., Carls et al. 1999; Lindén 1978; Kocan et al. 1996a; Heintz et al. 1999). Results have shown egg and larval stages to be especially sensitive to oil. Studies of oil impacts on fish eggs indicate positive correlation between egg mortality, and concentration of toxic oil compounds in water and exposure time of eggs to toxic compounds. One of the more extensively studied species in oil impact assessments is herring, which is the study subject of this thesis as well, or to be more precise, herring eggs.

Economic impacts of oil spills on fisheries have been studied to some extent. Most studies seem to concentrate on estimating the economic impacts from changes in landings after past oil spills (Garcia et al. 2009; Loureiro et al. 2006; Garza-Gil et al. 2006). A few prediction studies can be found as well. For example, Berenshtein et al. (2019) developed a prediction model using spatial and temporal data of oil spill trajectories to predict areas, where fishery closures would be put to effect. Their model only considered the effect of closures on fishermen revenue and neglected the effect of oil induced additional mortality on fish biomass, and consequently future catches.

Bayesian inference has been applied in many models, for both assessing oil spill impacts on herring populations and herring stock assessment (e.g., Rahikainen et al. 2017; Mäntyniemi et al. 2013a; Muradian et al. 2017). These applications have mostly focused on assessment of effects after past oil spills and development of population dynamics from historical data. Bayesian inference is based on the

Bayes rule (Gelman et al. 2014), which allows predictions to be made from estimated uncertain parameter values. Using Bayesian methods in a prediction model, allows the incorporation of uncertainty into decision making. There are very few studies available (e.g., Lecklin et al. 2011), in which a Bayesian inference model is used for predicting impacts of possible future oil spills on herring population dynamics. Furthermore, there are virtually no studies available, where a Bayesian inference model is used for predicting both possible oil spill impacts on herring population dynamics, and oil induced economic impacts on herring fisheries. Another characteristic missing in previous studies, is the integration of knowledge from laboratory studies into population level biological and economic predictions.

The aim of this thesis, is to develop a hierarchical Bayesian bioeconomic prediction model for predicting oil spill impacts on Baltic Sea main basin herring population through oil induced additional egg mortality, estimated from laboratory study data. In this study, the model will be used for different hypothetical oil spill scenarios, which will impact herring spawning grounds in coastal areas. The different scenarios vary in terms of the initial population state, and certain oil spill characteristics. The resulting effects on population abundance, biomass and catches are predicted and compared to a situation with no oil exposure. In addition, the economic values of the effects on biomass and catches compared to no oil exposure will be estimated. The goal is to define the economic impact of an oil spill on fishermen. The prediction model is built by modifying and combining existing models developed for 1. assessment of population dynamics, 2. meta-analysis on laboratory studies of oil induced additional herring egg mortality, and 3. oil spill impacts on fish populations.

1.2 Structure of the thesis

In the first chapter, some basic concepts of Bayesian inference are reviewed to make this thesis easier to follow. Then, some important aspects related to Bayesian inference modelling in fisheries stock assessment are reviewed. The Bayesian stock assessment model developed by Mäntyniemi et al. (2013a) will be used as the basis for developing the prediction model in this thesis. Therefore, it is important to understand the essential concepts related to Bayesian stock assessment.

In the second chapter, relevant literature on assessing oil spill induced herring egg mortality is reviewed, and the most important aspects are identified for the context of developing the prediction model. To calculate the financial losses to fishermen, relevant literature on herring pricing and economics is reviewed. Some important aspects to consider, when integrating an oil induced mortality model to a stock assessment model, are presented. Relevant theory on validating a Bayesian inference model is reviewed at the end of the chapter.

In materials and methods, the structures of the models used in this thesis, are described in relevant detail. The computational methods and their most important aspects are reviewed before presenting the results. After the results have been presented, they are discussed in the light of the reviewed literature. Finally, the study results are concluded in comparison to the aim of the study, and future directions are suggested.

1.3 Five steps of Bayesian inference

Bayesian inference is about reallocation of probability across possible values of parameters related to the problem being analyzed (Kruschke, 2015). In general, there are five steps in Bayesian inference (Figure 1). These steps will be followed throughout this paper.

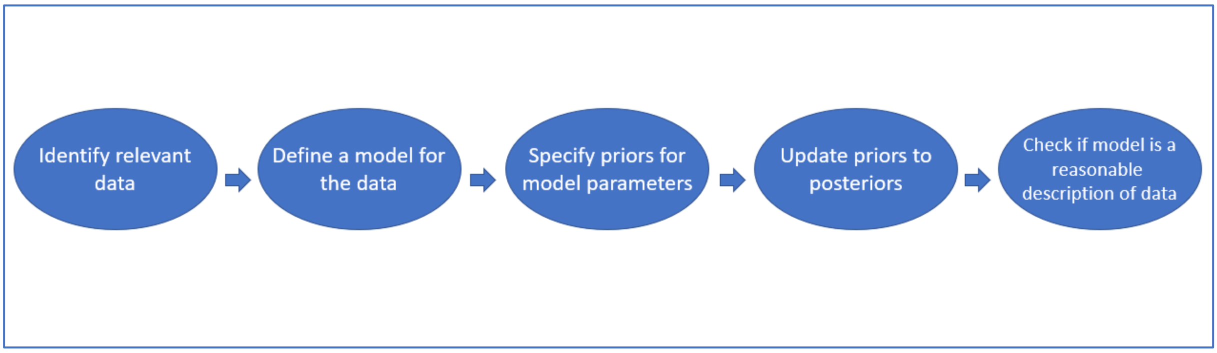


Figure 1, Five steps of Bayesian inference, (Kruschke, 2015)

When solving a scientific problem, a typical Bayesian inference starts with identifying relevant data. In practice, available data is never a perfect representation of the problem, and it is only a sample of the total population. In addition, measuring of the data is subject to error. Oberkampf, Helton, Joslyn, Wojtkiewicz and Ferson (2004) categorize uncertainty arising from randomness in processes, like measuring, as aleatory uncertainty, and uncertainty arising from imperfect knowledge as epistemic uncertainty. Epistemic uncertainty can in theory be reduced by gathering more knowledge through collected data and other information sources. These information sources may include, for example, publications or expert knowledge, which may be important if there is no appropriate observational data. (O'Hagan, 2019)

The goal of defining a model, is to describe the system as well as possible, from which the data is a sample of (Kruschke, 2015). A model consists of formulas that characterize trends and spreads in the system. The formulas consist of parameters that determine the mathematical forms of the trends and spreads. Therefore, the chosen mathematical formulas define which parameters need to be estimated. In the beginning there are usually several candidate models. The chosen model or models should be comprehensible in relation to the problem, with meaningful parameters. The mathematical form defined by the parameter values, should at least roughly resemble the system. The possible parameter values should be within a meaningful space for the chosen model.

In Bayesian inference, the meaningful parameter value candidates are assigned prior probabilities (Kruschke, 2015; Gelman et al. 2014). Prior probabilities, or priors, can be retrieved from, for example, previous research or expert elicitation by conducting interviews (Kruschke, 2015; Mäntyniemi et al. 2013a). Prior describes what the probabilities of the candidate values are believed to be before observing any data (Kruschke, 2015). Priors can hold various amounts of information. The more information a prior holds the more it assigns probability over a narrow range of candidate values, i.e., the prior is more accurate.

The priors are updated to posteriors using the Bayes rule (Figure 2). It calculates the probabilities of the candidate parameter values, after observing data. Posterior is the result of allocating probability to more credible parameter values given the data. Sometimes however, uncertainty can increase from prior to posterior, if the collected data contradicts the priors. The posterior shows the uncertainty related to possible parameter values by showing their probability distributions. Using posteriors as priors in future studies, offers a systematic and continuous learning possibility in science.

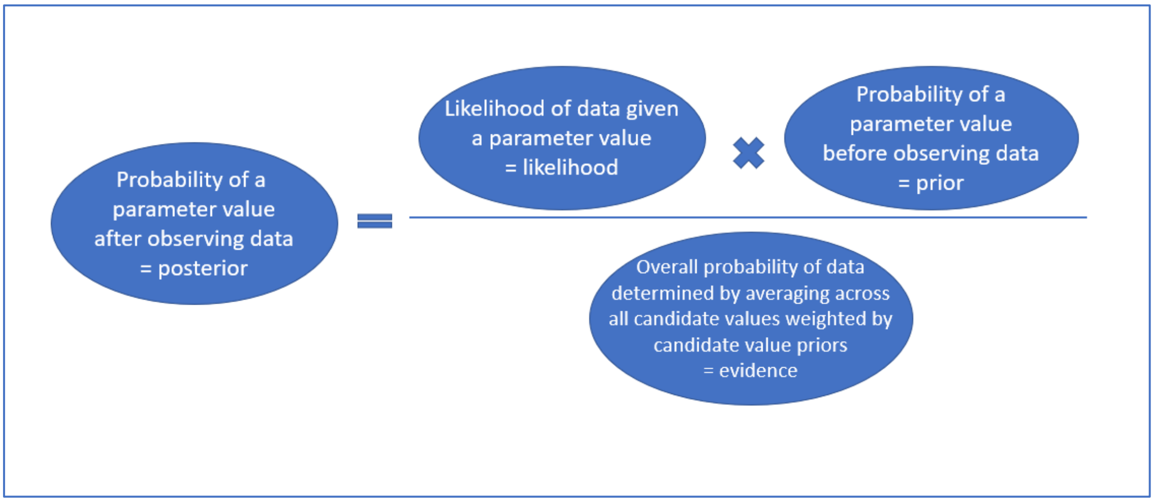


Figure 2, Bayes rule, (Kruschke, 2015)

The last step of Bayesian inference is to check whether the defined model, and its posteriors, describe the data reasonably well. This is done by simulating data with the model and comparing how much the simulated data deviates from the observed data. There are numerous ways to analyze this deviation. Before going into the steps of Bayesian inference in this thesis, some characteristics of Bayesian modelling in this study's context need to be reviewed, to understand the basis of the prediction model.

1.4 Bayesian modelling in fisheries stock assessment

In Bayesian modelling, a probability model is fitted to observational data and the results are summarized with probability distributions on model parameters and predictions (Gelman et al. 2014). Inferences are made according to these summaries. Advantages of Bayesian methods have been recognized in fisheries' stock assessment (Punt and Hilborn, 1997; McAllister and Kirkwood, 1998; Hammond and O'Brien 2001; Dorazio and Johnson 2003; Kuparinen et al. 2012; Mäntyniemi et al., 2013a). In a stock assessment model, the population dynamics of a fish stock are modelled into the parameters. In this paper, the terms stock assessment model and population dynamics model are used synonymously.

Bayesian model averaging

One of the main advantages of Bayesian methods, is the ability to incorporate model uncertainty as an integrated part within the stock assessment model, in the form of Bayesian Model Averaging (BMA) (Hammond and O'Brien 2001; Mäntyniemi et al. 2013a). BMA allows the inclusion of alternative models into the analysis, by weighting them according to their probabilities in the context of the problem being modelled. Geromont and Butterworth (2015) have stated that it is important for the realism of a stock assessment model to incorporate more than one stock-recruitment model into an analysis, by utilizing BMA, if the problem being analyzed so requires. In management of multinational fisheries, BMA allows all parties' advocated models to be considered in the complex environmental problems with multiple sources of uncertainty (Hamilton et al. 2009). The models must be chosen carefully for BMA, because some models might fit the data but make no sense ecologically. It is an important challenge to introduce theoretical knowledge to Bayesian models and model selection.

Hierarchical models

A Bayesian hierarchical model (BHM) considers the stochasticity and uncertainty inherent in fish population dynamics (Kuparinen et al. 2012) and furthermore, uncertainty of the parameter values can decrease faster in hierarchical model structures as data is accumulated. According to Gelman et al. (2014), a BHM is used in applications where multiple parameters can be assumed in a same group, according to the causal relationships of the problem.

The parameter groups in a BHM can be considered as fixed or random effects, depending on the aim of the analysis (Korner-Nievergelt et al., 2015). Fixed effects have a finite number of groups and a fixed effect study aims to compare the between-group differences of these specific groups. Random effects have theoretically an infinite number of groups, all belonging to a common population, from which the groups analyzed in the study are assumed to be a random sample of. The common population distribution is estimated with hyperparameters, to which the parameter groups have dependency to. Observations are used to estimate the parameter posteriors and aspects of the common population distribution. In a random effect BHM for stock assessment, hyperparameters are uncertain population dynamics parameters, and the parameter groups represent population states at different points in time, such as years, and are temporally dependent on the previous time points (Mäntyniemi et al., 2013a; Massiot-Granier et al., 2014) (Figure 3).

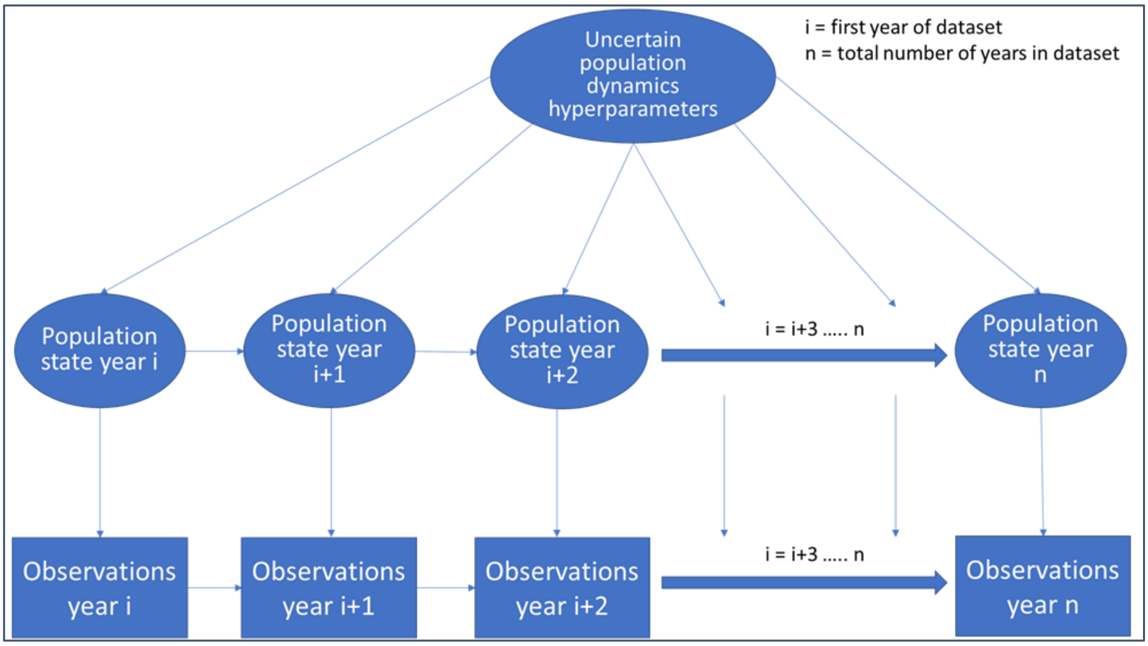


Figure 3, Illustration of a population dynamics BHM

Parameters in a BHM can be modelled as regression models. Shimoda and Arhonditsis (2015) studied modelling the group specific parameters with a regression model consisting of hyperparameters. According to Gelman et al. (2014), linear regression models are used in BHMs, when there are regression parameters on different hierarchical levels of variation, like in groups representing population states at different time points. Usually, the parameters values, estimated by regression models, are transformed. Transformation is done so the parameter value of interest would fit to the regression model (Kruschke, 2015).

BHM can include dynamic non-linear density-dependent stock-recruitment relationship assumptions in the form of, for example, Beverton-Holt or Ricker stock-recruitment functions, while utilizing BMA (Fleischman et al. 2013; Mäntyniemi et al., 2013a). Density-dependent models can add to the realism of the model if they are in accordance with the problem at hand (Massiot-Granier et al. 2014). According to Millar and Meyer (2000), traditional stock assessment models are often assumed linear, and process error is assumed as normally distributed. This is because calculating the integral of the marginal likelihood function, or evidence (Figure 2), over all possible parameter values, is extremely demanding. In Bayesian models, the linearity and normality assumptions are not necessary because of developments in sampling methods, like Markov Chain Monte Carlo (MCMC).

BHM can be built as fully age-structured considering growth and size of fish in each year class, and their interdependencies and effect on recruitment (Mäntyniemi et al. 2013; Massiot-Granier et al. 2014). A fully age-structured model is crucial in predicting how population dynamics react to different management decisions or stressors (Kuparinen et al. 2012). According to Hillary (2011), using a fully age-structured model, allows to model survival of a fish population as a time-varying parameter, and to model the survival of different age-classes separately. According to Kuparinen et al. (2012), growth and size at age, should be modelled as dependent stochastic variables, size being hierarchically dependent on growth. Natural and fishing mortalities should in turn be modelled as stochastic variables dependent on size.

Prior specification

According to Shimoda and Arhonditsis (2015), there are many options for the specification of priors. They can be considered as “non-informative”, or vague, if knowledge about the parameters is low. A prior is informative if there is useful prior knowledge coming from, e.g., existing publications or such stock assessments, where the assessed species is somehow comparable to the species being analyzed. According to Gelman et al. (2014), in most real-world problems there should be enough knowledge to at least constrain the possible parameter values to a finite range. It is very rare to be the first scientist to study a certain topic and therefore, there is almost always at least some prior knowledge. According to Shimoda and Arhonditsis (2015), if the knowledge of the parameters is received from the data that is also used to update the prior, then the information in the data would be used twice. According to Gelman et al. (2014), doing a Bayesian analysis with this kind of prior specification can only be considered an approximation of a complete Bayesian analysis.

Group level parameters can be given a multivariate prior, if the correlation between the parameters needs to be considered (Shimoda and Arhonditsis, 2015). According to Gelman et al. (2014), multivariate priors are often used with regression models when, for example, the intercept and slope of the regression function vary by group. In a multivariate prior, variation of the parameters is considered in the form of a covariance matrix.

Experimenting with the model using different priors for parameters, can point out specific parameters to which the conclusions made with the model are sensitive to (Gelman et al., 2014). Muradian et al. (2017) developed an age structured BHM stock assessment model for Prince William Sound (PWS) herring population. They concluded that the model was sensitive to natural mortality assumptions, indicating the importance of prior knowledge of this parameter. Ibaibarriaga et al. (2008) developed a BHM for anchovy stock assessment. They stated that they need to develop certain model priors to be more informative by using expert elicitation for prior specification. Priors are often based on expert elicitation (O'Hagan, 2019).

Prediction models

Decision making in fisheries management requires estimates of parameters and forecasts of uncertain variables, like biomass and fishing mortality, while considering uncertainty (Ludwig et al. 1993). These requirements are inherent in Bayesian methods (Dorazio and Johnson 2003). Hamilton et al. (2009) argued that using BMA and carefully selecting environmental covariates for regression parameters, sum up to more accurate predictions. It is crucial to decide how much prior probability is given to each model in BMA, and how the priors are specified.

A parameter estimation model can be used to predict unknown quantities, such as future observations or future values of population state parameters (Gelman et al. 2014). This is done by using the estimated posterior distributions on parameter values for forecasting the unknown quantities from the posterior predictive distributions, using the formulas defined for the parameters and observation models. (Figure, 4).

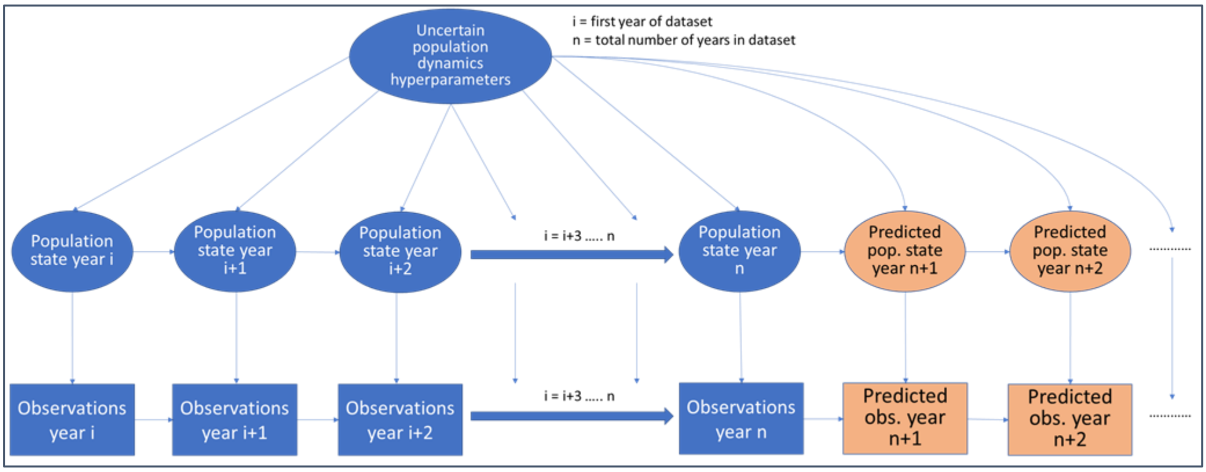


Figure 4, Illustration of prediction with a BHM

Several Bayesian state-space models have been used for prediction. Geromont and Butterworth (2015) used their models for data poor fisheries to predict the outcomes of different management actions ten years into the future. Ibaibarriaga et al. (2011) used their model to predict the probabilities of biomass being under a certain level under fixed recruitment and catch scenarios. Fleischman et al. (2012) predicted the run size of Karluk river salmon one year into the future. Muradian et al. (2017) compared their biomass predictions to those done with the current stock assessment model of Alaska Department of Fish and Game. They concluded that the advantage of using a Bayesian model, is being able to regulate according to probability intervals or cumulative probability distributions, instead of point estimates, which could leave out possibly vital information.

Relevant findings of this chapter

In a stock assessment model built as a random effect BHM, hyperparameters consist of uncertain population dynamics parameters, and parameter groups represent population states at each time step of the observations. If the problem at hand requires so, it is important to include more than one possible, possibly density dependent, stock-recruitment model into the analysis by utilizing BMA. A fully age structured BHM can add to the realism of the model and makes it possible to model size and survival as age-specific parameters. A BHM can be used to predict population states in the future.

In this thesis, a generic Bayesian stock assessment model developed by Mäntyniemi et al (2013a) is used as the basis for the prediction model that will be developed in this thesis (Figure 5). The structure of Mäntyniemi et al.'s model includes most of the important aspects of a population model discussed above. It includes stakeholder knowledge in informative priors. It utilizes BMA for the density dependent stock-recruitment part of the model. Process variations in natural mortality, growth parameters and fishing mortality are treated as uncertain parameters, in contrast to some earlier stock assessment models (Nielsen & Lewy, 2002). Furthermore, the model is a fully age structured random effect BHM. The structure of the model will be described in more detail in materials and methods.

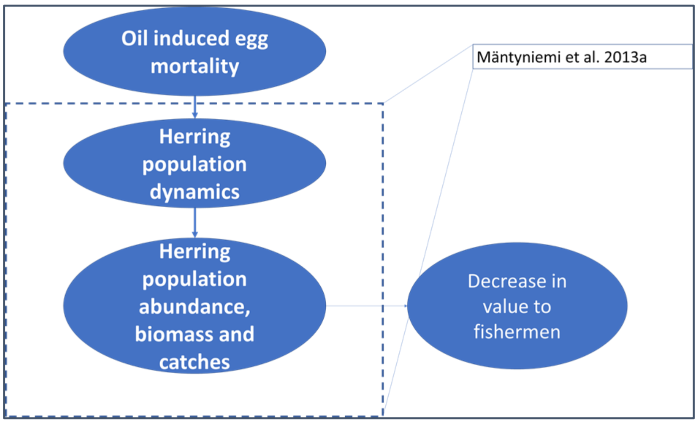


Figure 5, Illustration of the prediction model

In the next chapter, the steps of the Bayesian inference (Figure 1) of this thesis are started by reviewing relevant literature for the oil induced egg mortality-part, and the decrease in value to fishermen- part of the prediction model. As more relevant aspects for the prediction model are found in literature, they will be appended to the model, which will be illustrated in the summaries of the sections.

2 Identifying relevant data

The aim of the modelling in this thesis, is to build a bioeconomic model for describing the impacts of oil on fish stocks and fisheries. For this purpose, before reviewing the literature, relevant questions related to the study were recognized to which the data should shed light on (Figure 6). These questions are followed throughout this chapter.

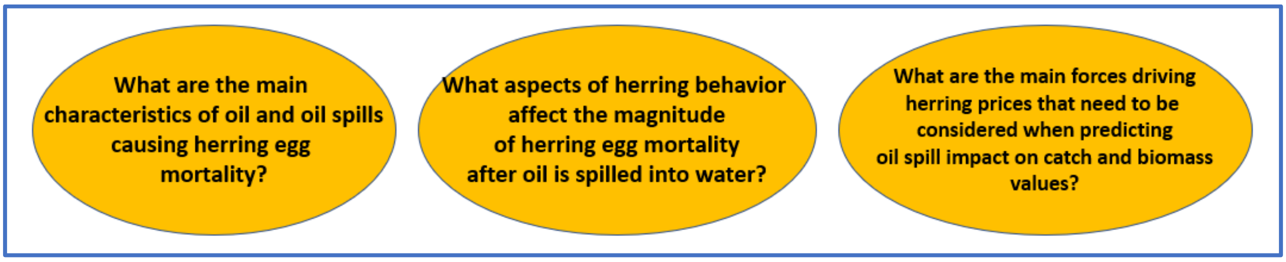
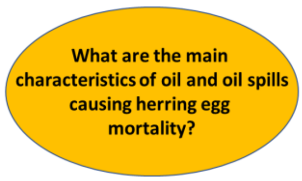


Figure 6, Relevant questions for identifying relevant data

2.1 Oil toxicity on herring eggs



2.1.1 Oil weight and type affect the proportions of toxic compounds in oil

Polycyclic aromatic hydrocarbons are the most toxic compounds in oil

There are about 17 500 different compounds in oil, and of these compounds, aromatic hydrocarbons are most likely the most toxic to herring eggs (Fingas et al. 2011, Wiens et al, 2013). According to Neff et al (2000), the most toxic aromatic hydrocarbons are monocyclic aromatic hydrocarbons (MAHs), which contain one aromatic ring, and then polycyclic aromatic hydrocarbons (PAHs), which contain two or more aromatic rings. Therefore, the number of aromatic rings has negative correlation with the toxicity of the compound. MAHs are very volatile and do not persist in water very long. According to Heintz et al. (1999), when the persistence of the compound is considered, the most toxic aromatics are most likely compounds containing three and four aromatic rings. They are sufficiently reactive and persist relatively long in the environment and embryos. In studies of oil effects on marine biota, the chemicals under investigation are often PAHs. Commonly reported quantities are total polycyclic aromatic hydrocarbon (TPAH) concentrations, total petroleum hydrocarbon (TPH) concentrations and sum of some specific PAHs' concentrations (Table 2). Laboratory experiment results have indicated positive correlation between initial TPAH concentration in water, and mortality and sublethal effects (Linden 1978; Carls et al. 1999; Kocan et al. 1996b).

Oil products are divided into classes according to their weight, and into types according to their refinement stage

Oil products are often classified according to their specific gravities converted to API (American Petroleum Institute) gravities (ITOPF, 2002). Oil product's gravity tells, for example, whether it will sink or float (Wiens, 2013). As the API gravity of an oil product increases, it becomes lighter and vice versa. If an oil product has API gravity of 20 or higher, it is considered medium or light, and if lower than 20 it is considered heavy. (Wang and Stout, 2007) These API boundaries may vary across different studies (see e.g., ITOPF, 2002). Medium and light oils float on water and form a layer on the surface, and heavy oils can sink after the lighter compounds have evaporated (Fingas et al 2011; Wiens 2013; Guitart et al. 2008).

According to Boehm et al. (2013), crude oils and refined fuel oils are usually the oil types involved in oil spills. The type of an oil product influences the amount and type of PAHs it contains (National Research Council, 2003; Wang and Stout, 2007). An oil product can contain between 0 and 60 percent PAHs out of TPH (Fingas, 2011). The different proportions of PAHs influence, for example, the compound's volatility and solubility, and consequently the concentrations of PAHs found in water column after a spill (Wiens, 2013, Table 1).

Associated spill	Measured compounds	Measured concentration (in ppb)	Oil amount spilled (tonnes)	Oil type	Reference
Exxon Valdez	*TPAH*	*0.1 - 12*	*35500*	*medium crude*	*Wolfe et al. 1994*
Exxon Valdez	*TPAH*	*0.1 - 41.6*	*37000*	*medium crude*	*Boehm et al. 2013*
Exxon Valdez	*TPAH*	*0.01 - 30*	*34600*	*medium crude*	*Neff and Stubblefield 1995*
North Cape	*TPAH; TPH*	*13.7-115; 113-3940*	*2700*	*light fuel*	*Reddy and Quinn 2001*
MSC Napoli	*TPAH*	*0.01 - 57*	*200*	*heavy fuel*	*Guitart et al. 2008*
Prestige	*TPH; 25 individual PAH*	*0.05 - 28.8; 0.07 - 9.56*	*77000*	*heavy fuel*	*Gonzales et al. 2006*
Bahia Paraiso	*TPAH*	*50 - 100*	*531*	*light fuel*	*Kennicut et al 1991*
Baltic Carrier	*TPAH*	*0,64 - 12,8*	*2400*	*heavy fuel*	*Pecseli et al. 2003*
Antonio Gramsci	*N/A*	*N/A*	*570-650*	*heavy crude*	*Nissinen 2000; Lecklin et al. 2011*

Table 1, Water column oil compound concentrations after past oil spills

Polycyclic aromatic hydrocarbon composition determines toxicity of oil

Linden (1978) studied the effects of three different oil products on herring eggs, refined light no. 1 fuel oil, Tuimaza crude oil and Venezuela crude oil. According to the results, only no. 1 fuel oil in concentrations of at least 5 parts per billion (ppb) caused significant egg mortality. Anderson et al. (1974) tested the toxicity of two different crude oils and two different refined fuel oils to marine biota. Water-soluble fractions of the refined products were in all cases more toxic. Light refined fuel oils, such as diesel fuel and no. 1 fuel oil, contain PAHs which are dominated by two- and three-ringed compounds, such as naphthalenes and chrysenes (National Research Council, 2003). For this dominance, light refined products have the biggest potential among oil products to harm aquatic biota. Heavy refined products in turn, have the smallest water-soluble fraction of all the oil products, and thus lowest toxicity.

Crude oils have a wide variety of different PAH compositions that are usually dominated by naphthalenes and chrysenes, but to a lesser extent than light refined products (National Research Council, 2003; Wiens, 2013). Heavy crude oils generally contain more PAHs in total than lighter crude oils, but with higher proportions of less soluble compounds (Wang and Stout, 2007). Important PAHs to consider in analyses of oil toxicity to herring eggs, are more volatile and soluble PAHs. Lighter crude oils are on average more soluble than heavy crude oils (Fingas, 2011). Due to the wide variety of PAH compositions in crude oils, their compositions of water-soluble PAHs should be determined case by case for each individual spill.

2.1.2 Weathering and movement of oil influence the concentration of toxic compounds in water and exposure time of herring eggs to them

When oil enters water after a spill, it moves and undergoes weathering (Fingas et al. 2011). The rate of weathering is mostly affected by oil type and weight. Weathering consists of processes changing the physical and chemical properties of oil. Weathering processes include evaporation, emulsification, natural dispersion, dissolution, photo-oxidation, sedimentation, adhesion, interaction with minerals, biodegradation, and formation of tar balls. As MAHs weather away, the contribution of PAHs to the toxicity of an oil product increases, starting from the two- and three-ringed compounds (Wiens, 2013; Fingas et al. 2011). Neff et al. (2000) argue however, that MAHs and PAHs cause less than 50 % of the toxicity of weathered crude oils, and the rest is most likely caused by an unresolved complex mixture and resins. Part of oil’s toxicity might be due to products created when oil compounds biodegrade (Neff et al. 2013). According to Middaugh et al. (1998), biodegradation products more likely cause long term sublethal effects rather than mortality.

Dispersion transfers oil from the surface to the water column

Oil weight and weather conditions affect the formation of oil water dispersion (OWD). According to Fingas et al. (2011), OWD forms when fine oil droplets are transferred into the water column by wave action. Dispersion is more significant when sea energy increases, and when the oil product is lighter. OWD most likely resembles the oil-water mixture formed right after a spill (Kocan et al. 1996a). According to Anderson et al. (1974), dispersed oil hydrocarbons in the water column undergo a transition to solution. This transition is affected by oil type and the amount of excess oil available on the surface. Refined products form toxic solutions with much less oil than crude oils. Support for this statement comes from the fact that in some larger spills involving crude oils, the effects on biota have been smaller than in smaller spills involving refined products (Table 2).

Dissolution increases PAH concentration in water

Dissolution can sometimes be a significant weathering process if the spilled oil is light, and thus contains large amounts of soluble components, like the spilled oil in the North Cape oil spill (Reddy and Quinn 2001; Fingas et al 2011). After the Bahia Paraiso spill, TPAH concentrations were relatively large due to the spilled oil being diesel fuel (Kennicut et al. 1991). Days after the Baltic Carrier oil spill, TPAH concentrations near the spill site were higher than background levels, but rapidly declined during two months after the spill (Pecseli et al. 2003). The spilled oil had relatively high proportions of volatile and soluble low molecular weight PAHs and MAHs.

Usually, dissolution happens to only a fraction of a percent of the spilled oil but, for example, in the North Cape spill natural dispersion of the oil by strong wave action aided the dissolution. This could have explained the relatively high concentrations of TPAH in the water column (see Table 2) and the significant negative impact on biota in the spill area (Fingas et al. 2011; Reddy and Quinn 2001). After the Exxon Valdez spill, there was a storm in the spill area. About 23 % of the spilled oil was dispersed (Wolfe et al 1994; Reddy and Quinn 2001). According to Neff and Stubblefield (1995), only 1,6 % of samples collected, collected after the storm, showed concentrations of TPAH over 1 ppb. The Exxon Valdez oil had less soluble PAHs than the North Cape oil (Wang et al. 1999; Reddy and Quinn 2001).

Increasing exposure time to PAHs increases egg mortality

The exposure time of eggs to PAHs has been recognized as an important factor related to egg mortality and sublethal effects (Linden, 1978; Carls et al., 1999). According to Carls et al. (1999), as exposure time increases, incubation time decreases while mortality and abnormalities increase. Their results indicated differences between PAHs regarding the needed exposure time to them to induce mortality. The differences in exposure times were affected by the molecular weights of the compounds. Herring eggs react more quickly to MAHs and light PAHs (Heintz et al. 1999). The uptake of three- and four ringed PAHs by eggs is slower. Once these larger compounds enter the eggs however, they remain there for longer time periods causing toxicity. As oil weathers, the PAH composition becomes more dominated by three- and four-ringed compounds.

Movement of oil can bring toxins to herring spawning grounds

Oil weight and type affect the movement of oil after it enters water (Fingas, 2011). Floating oil spreads into a slick over the surface. Lighter products, especially refined oil types, spread more rapidly and to a larger extent. Oil spreads even without wind or currents due to gravity and interfacial tension between oil and water. Wind and currents can speed up the process of spreading and cause the oil slick to move along the water surface. Movement, spreading and vertical dispersion of oil determine the location where the oil ends up after a spill. If it ends up in herring spawning grounds, it may cause oil induced herring egg mortality (Wolfe et al. 1994; Kocan et al. 1996b; Aneer & Nellbring. 1982; Brown et al. 1996; McGurk and Brown, 2011; Incardona et al. 2012; Barron et al. 2003).

Relevant findings of this section

The reviewed literature in this section has revealed several relevant subjects (Figure 7).

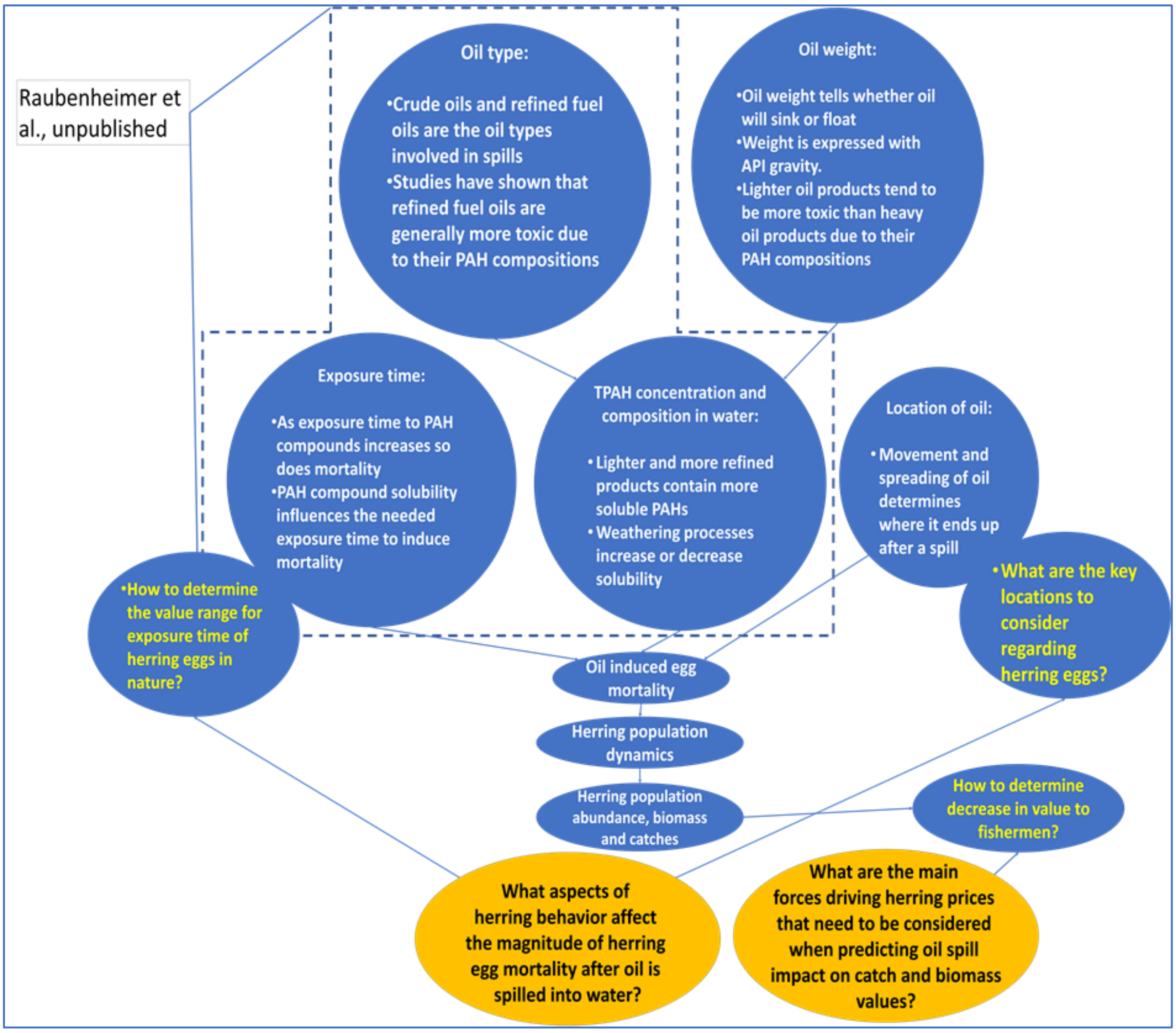


Figure 7, Summary of oil and oil spill characteristics causing herring egg mortality in the prediction model illustration and remaining open questions

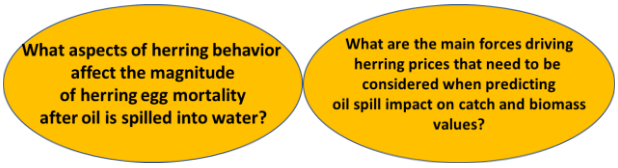
Oil induced herring egg mortality seems to be dependent on concentration of soluble, and somewhat persistent PAHs in water, and exposure time of eggs to these compounds. Exposure of herring eggs to PAHs is dependent on movement and spreading of oil bringing it to spawning grounds. The PAH composition of an oil product, and its solubility, is dependent on oil type, and consequently its weight. The model developed in this study needs to consider these aspects in its structure.

Raubenheimer et al. (unpublished) developed a Bayesian meta-analysis model for assessing oil induced additional mortality on herring eggs. The meta-analysis model considers many of the relevant subjects described above, and it will be modified and extended for the purpose of this study. The modified version of the meta-analysis model that will be developed in this thesis, will be used as the oil induced additional mortality part of the prediction model. The meta-analysis model by Raubenheimer et al. (unpublished) analyzed the oil type specific additional mortality of herring eggs, as dependent on exposure time and concentration of PAHs in water. The results of the analysis indicated generally positive correlation between initial concentration of PAHs in water and mortality of eggs. Exposure time generally correlated positively with mortality as well. The model will be modified to include the effects of oil weight and location of oil spill, among other things. The original meta-analysis model and its modified version will be described in more detail in materials and methods.

Remaining open questions

After reviewing the literature in this chapter, a few open questions remain (Figure, 7), for which more relevant literature needs to be reviewed. The meta-analysis model in Raubenheimer et al. (unpublished) does not consider the effect of an oil product's weight on additional mortality. In addition, the location of an oil spill in relation to location of herring eggs, is not yet included in the meta-analysis model. In the next chapter, literature on these subjects will be reviewed. Since oil induced mortality is an additional source of mortality, herring egg natural mortality literature will be reviewed, for determining the baseline mortality. In addition, literature on how to assess the effect on value to fishermen will be reviewed.

2.2 Baltic Sea Herring



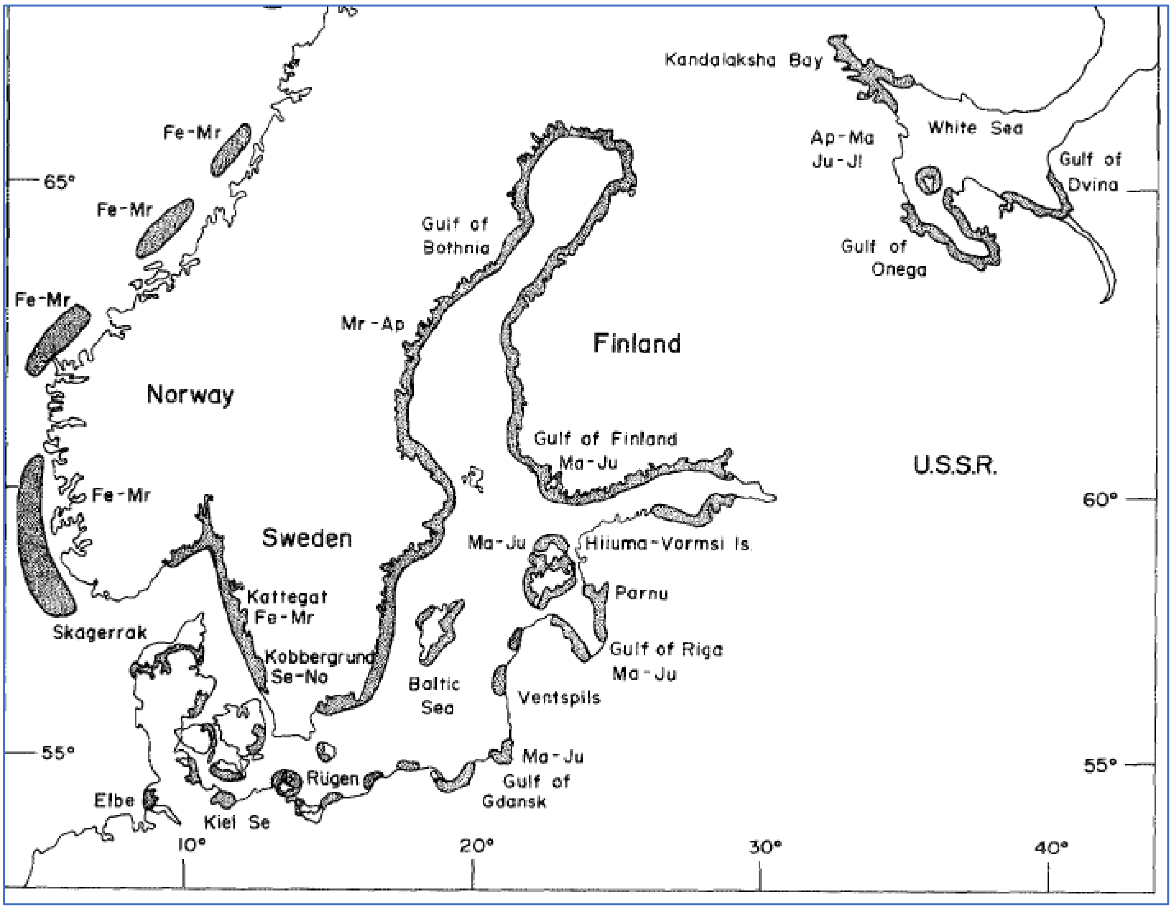
Natural mortality of herring eggs varies in nature

When analyzing the oil induced additional mortality on herring eggs, it is important to separate it from the natural mortality of eggs. Studies on herring egg natural mortality have reported very varying results (Table 2). Rajasilta et al. (1989) found that mortality of herring eggs in Finnish archipelago varied according to the substrate they were attached to. Aneer (1987) has stated that the major cause of natural mortality in the Baltic Sea could be toxic algal exudates. Rajasilta et al. (1989) also found that in their samples, the total amount of eggs had no significant effect, but depth and temperature were positively correlated with mortality. Good oxygen conditions and not too high temperature appear to be crucial for egg survival. In many studies, the predation of herring eggs, and wave and current action, have been stated as significant sources of herring egg mortality (Richardson et al. 2011; Hempel 1971; Moll et al. 2018).

Region	Expected value	Value range	Reference
Baltic Sea	*9,52 %*	*0,0 % - 95,2 %*	*Rajasilta et al (1988)*
Northern Pacific Ocean	*14,68 %*	*10,58 % - 18,79%*	*McGurk and Brown (2011)*
Baltic Sea	*33 - 74 %*		*Aneer (1989), Aneer (1985)*
Atlantic Sea, laboratory	*78 %*	*14 % - 100 %*	*Taylor (1971)*
Atlantic Sea	*97 %*	*95 % - 99 %*	*Dahlberg (1979)*
Pacific Ocean	*13 %*		*Jones (2011)*
Pacific Ocean	*41,20 %*	*28,2 % - 52,2 %*	*Kocan et al. (1996)*

Table 2, Natural mortalities of herring eggs during incubation time

According to Haegele and Schweigert (1985), there are spring and fall spawners among Baltic Sea herring (Picture 1). In the western Baltic Sea, according to some evidence, there are two groups of spring spawners and one group of fall spawners (Popiee, 1958). According to one source, there are six groups of spring spawners in the eastern Baltic Sea (Rannak, 1971). From the eastern Swedish coast to Bothnian Sea and all the way to Gulf of Finland, spawning happens most likely in spring (ICES, 1979). Most likely the only fall spawning group in the eastern Baltic Sea, is in the Gulf of Riga.

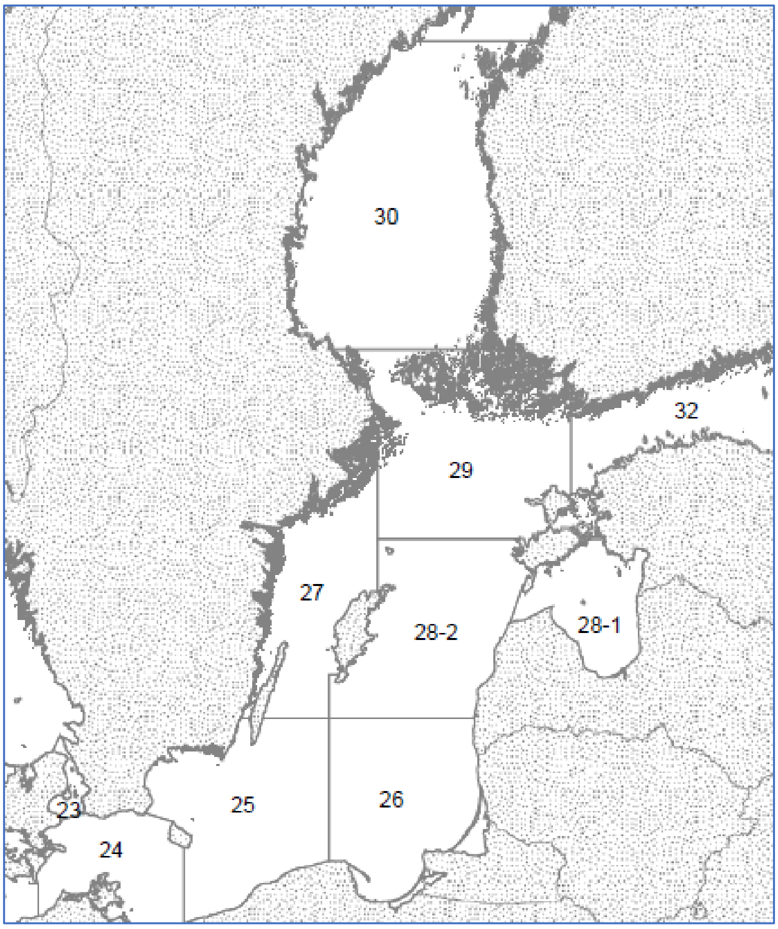


Picture 1, Spawning sites of Baltic Sea herring and local spawning time frame, (Haegele & Schweigert, 1985)

Regarding some characteristics, the spawning of Atlantic herring is suggested to be similar in all regions (Rannak, 1971; Drapeau 1973). Spawning appears to happen in high-energy environments, i.e., in areas with shallow shores, and with wave action or tides. Spawning in shallows in the Baltic Sea, takes place in depths of 0.4 – 12 meters (Rannak, 1971; Aneer and Nellbring, 1982). Depth depends on the starting time of spawning. If spawning starts later, the depth is usually greater because of higher surface water temperatures. The eggs sink to bottom and stick to substrates such as sand, gravel, stones, or seaweeds (Bigelow and Schroeder, 1954). Number of eggs has significant negative correlation with depth (Rajasilta et al. 1989). In surface or near-surface spills, the highest PAH concentrations are usually measured in the first few meters of the water column, and the concentrations decrease significantly after 10 meters (Boehm et al. 2013). Therefore, if oil moves to a herring spawning site during egg incubation, especially if the eggs are spawned by spring spawners, they are likely to get exposed to oil. Knowledge of timing of spawning in relation to timing of oil accident is crucial, as is the overall amount of oiled coastline in herring spawning grounds (Lecklin et al. 2011).

According to Geffen (2002), herring eggs' hatching started after 16 days and ended after 18 days in water temperature of 7 ºC. Bigelow and Schroeder (1954) state, herring eggs' incubation time can be up to 40 days depending on temperature. In temperature of 3 ºC incubation can even last 40 days, in 7 ºC 15 days, and in 10 ºC 11 days on average. Knowing the incubation time of herring eggs is vital since exposure time to PAH compounds is positively correlated with egg mortality (Carls et al. 1999; Heintz et al. 2000). The incubation time of herring eggs ultimately determines the range of possible values for exposure time of eggs to PAHs.

In the Baltic Sea, cod, herring, and sprat constitute about 95 % of total fish catches (ICES, 2016). According to ICES (2019a), herring spawning stock biomass has shown an increasing trend since 2003 after a long decreasing trend (Figure 8) in ICES subdivisions 25-29 and 32 (Picture 2), but catches have been above maximum sustainable yield (MSY) since 2007. Stock assessment made by Mäntyniemi et al. (2013a), suggests there has been no decreasing trend before 2003, and herring biomass has remained stable from 1975.



Picture 2, ICES subdivisions in the Baltic Sea, (Anderson et al. 2011)

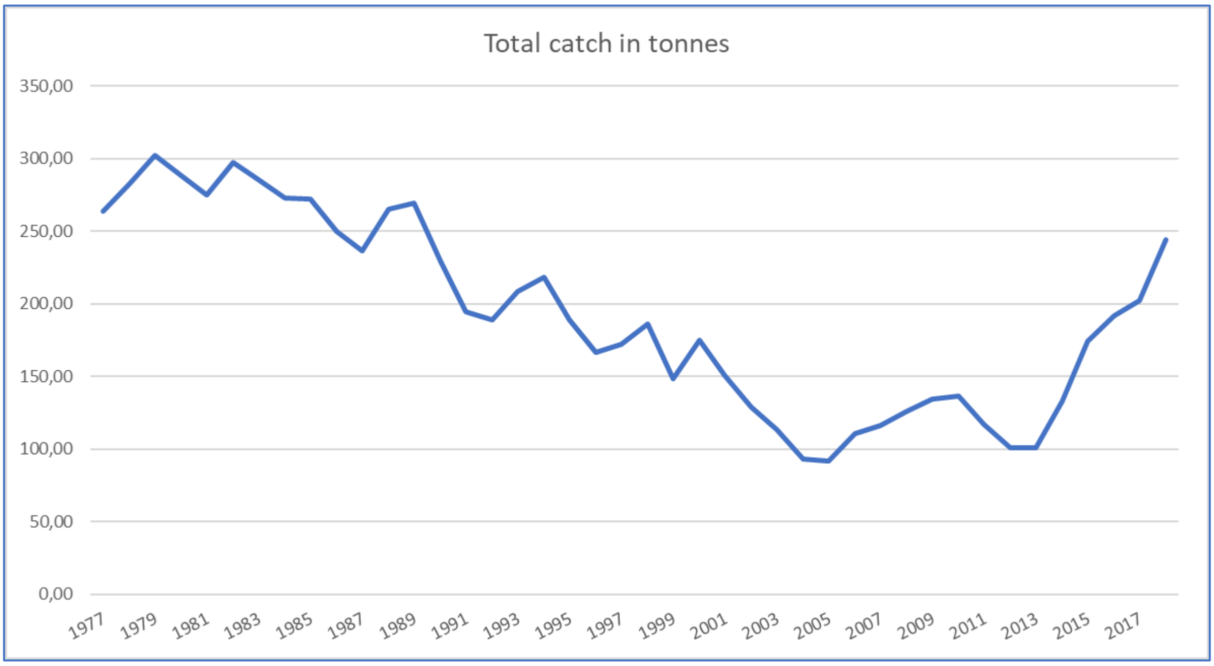


Figure 8, Development Baltic Sea herring catches in subdivisions 25-29 and 32, (ICES 2019b)

Fisheries management in EU is based on national total allowable catches (TAC), which are determined by the state of the fish stocks. The TAC is further divided into national quotas. The national quotas are further allocated to fishermen as transferable individual quotas (ITQ). (Aps et al. 2019) Biomass is an important metric used in assessing the state of herring stocks, and state of a stock directly affects TAC (Aps et al. 2019). Therefore, any changes in herring stock biomass will affect the income of fishermen.

Average first sale prices have remained stable in the Baltic Sea region countries, despite of changes in the local supply of herring (Figure 8 and 9). First sale price is what fishermen get when they sell herring from their catches. The average first sale price includes prices received from selling herring of all size classes, and to all purposes. The market for herring has changed in past decades (Aps et al. 2019). According to Pihlajamäki et al (2016), majority of herring caught in the Baltic Sea is sold for fur animal food and to other animal and fish feed industries. The dioxin related restrictions can influence where herring can be sold (Ignatius and Haapasaari, 2016). Fishermen generally get a better price for herring sold to consumer use than to industrial use (Ignatius and Haapasaari, 2016; Luonnonvarakeskus, 2020).

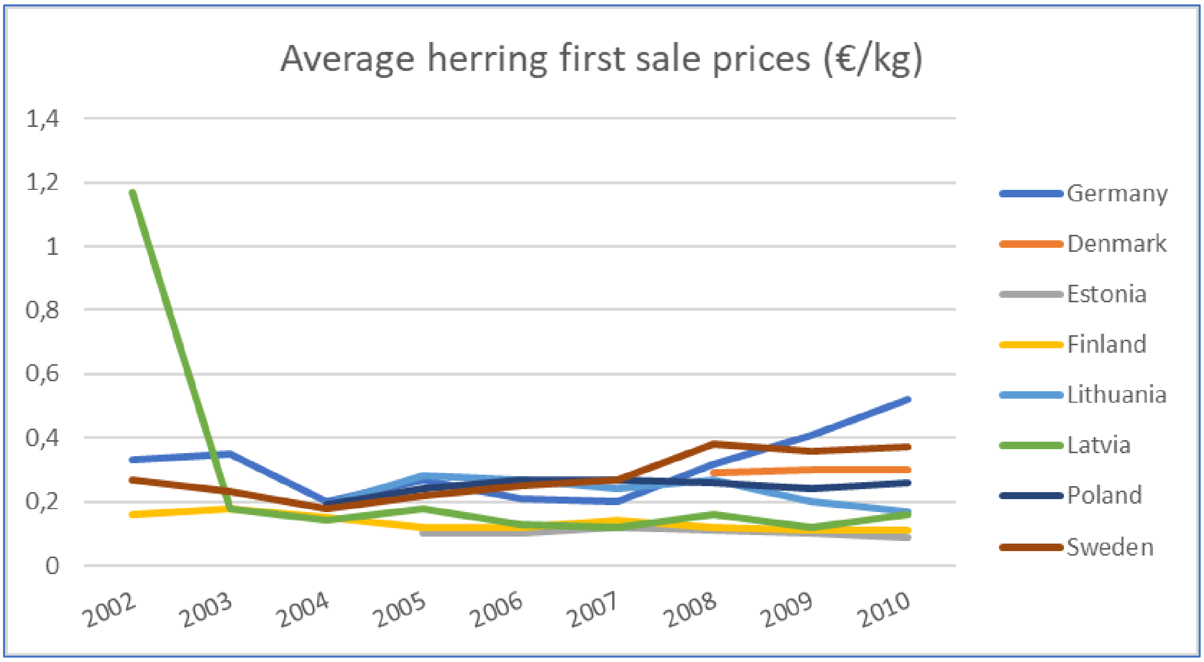


Figure 9, Development of Baltic Sea herring first sale prices, (Anderson et al. 2011)

Aps et al. 2019 have studied the different forces driving herring market these days. According to them, the development of the global market demand and stock states globally, are the most important drivers of herring market in the long run. Trade politics, demand of industries like fur industry, and changes in consumer behavior are now shifting the sources of demand globally. Furthermore, when the market is global, the most important factors affecting price of herring locally on short term, are changes in consumer behavior and changes in the demand and regulation of industry products like fur.

Relevant findings of this section

The range of possible values for the exposure time of herring eggs to PAH compounds, is limited by herring egg incubation time (Figure 10). When analyzing oil induced egg mortality, the incubation time needs to be estimated according to water temperature during the spill. Baltic sea herring spawn in shallow shores. To analyze oil induced mortality on herring eggs, the proportion of oiled coastline in herring spawning grounds needs to be estimated. The first sale price fishermen get from selling herring forward, most likely remains stable despite of changes in the local supply. Therefore, an oil spill induced change in supply probably does not affect local first sale prices. The decrease in the future income of fishermen can thus be estimated using the usual variation of first sale prices as a parameter.

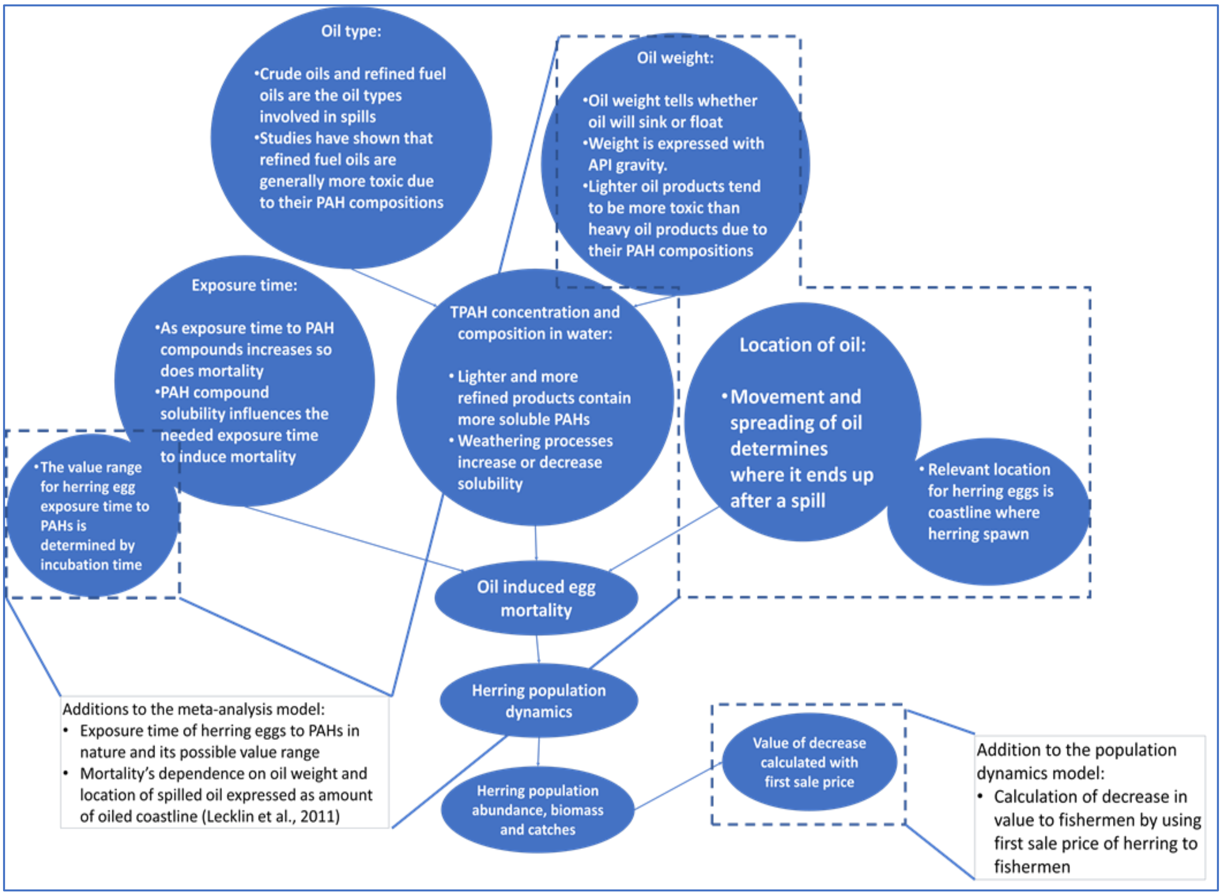


Figure 10, Summary of all the relevant subjects appended to the illustration of the prediction model

Before going into the next step of Bayesian inference (Figure 1) of this thesis, ways of integrating an oil induced mortality model into a population dynamics model needs to be researched. Relevant model checking methods in literature are reviewed as well. These model checking methods will be used in the last step of Bayesian inference of this thesis, before using the model for prediction.

2.3 Integrating oil induced mortality into a population dynamics model

Only a few Bayesian population dynamics models can be found in literature, which are developed for assessing oil spill impacts on marine life. The models usually include an additional mortality rate, or survival rate reduction, parameter within the population dynamics model. Schwacke et al. (2017) built an age-, sex- and class-structured population model for bottlenose dolphins. They modelled the mortality caused by Deepwater Horizon (DWH) spill as a survival rate reduction parameter in one class of dolphins, which was exposed to DWH oil. Muradian et al. (2017) developed a Bayesian stock assessment model for Prince William Sound (PWS) herring, which included modelling of possible oil spill impacts after the Exxon Valdez spill. PWS herring population spawning stock biomass (SSB) collapsed in 1993 and has persisted low ever since. For years 1992 and 1993, the researchers included additional mortality rates required to explain the sharp decline in SSB, which was assumed to be caused by, among other stressors, the possible oil spill impacts.

Lecklin et al. (2011) used a Bayesian model to analyze biological impacts of hypothetical oil spill accidents in the Gulf of Finland (GoF). Their model was used to assess impacts of two spill scenarios. In the analyses, the accident was assumed to have happened with no uncertainty. The important uncertain variables related to an accident, were size of tanker and cargo, type of oil, location of the accident, type of accident and timing of accident. Variable used for determining the location of a spill, was the proportion of oiled coastline. They concluded that this method is incomplete, and many other factors such as weather conditions can affect the amount of oiled coastline. Considering the spawning sites of Baltic herring identified in the previous section, in this thesis the location of spilled oil in relation to herring eggs is analyzed by the proportion of oiled coastline as well.

Rahikainen et al. (2017) integrated the oil spill impact model of Lecklin et al. (2011) into the population dynamics model developed by Mäntyniemi et al. (2013a). They modelled the oil induced mortality after the 1987 M/T Antonio Gramsci oil spill on herring offspring and adult herring, as additional mortality parameters in the year of the accident. In this thesis, the methodology used by Rahikainen et al. (2017) is adapted and explained in materials and methods.

2.4 Model checking

Posterior predictive checking

According to Gelman et al. (2014), a comprehensive analysis using Bayesian methods, should always include at least some kind of checking for fit of the model to data, and the plausibility of the model for the problem in question. One possible way to check fit to data, is posterior predictive checking, in which a replicate data set is created from the posterior predictive distribution, which is then compared to the actual observations using a suitable test statistic. Hillary (2011) simulated observations, and calculated median absolute deviation as a test statistic, for the calculation of Bayesian p-values. The Bayesian p-value tells the probability of the simulated data being more extreme than the observed data (Gelman et al. 2014). There are many possible test statistics to be chosen depending on the specific structure of the problem. If the p-values are equally distributed between 0 and 1 and are 0,5 on average, the variability is similar between the simulated data and the observed data.

Sensitivity analysis

According to Gelman et al. (2014), sensitivity analysis can be used to check the effect of using other possible models for calculating the posterior distributions. Millar and Mayer (2000) stated that a set of competing models can be derived with sensitivity analysis by specifying different sets of priors. Sensitivity analysis can be used for finding out the parameters to which information should be added, to make the posterior distributions more accurate. Massiot and Garnier (2014) found that their model was highly sensitive to changes in harvest rate priors, which hierarchically affected the rates of salmon returning to spawn, and consequently the whole stock abundance. Ibaibarriaga et al (2008) tested their model with posterior predictive checking, allowing them to see the model’s sensitivity to certain parameters, and helped them to adjust assumptions on them. Michielsen and McAllister (2004) conducted a sensitivity analysis on priors of stock-recruitment function steepness parameters. The comparison between different models was done by posterior predictive checking and calculating Bayesian p-values.

3 Materials and methods

3.1 The models

This section describes the models used and developed in this thesis (Figure 11). The meta-analysis model developed by Raubenheimer et al. (unpublished), will be described in sufficient detail and furthermore, how it will be modified for the purpose of this study. Relevant parts of the population model developed by Mäntyniemi et al. (2013a) will be described. The prediction model developed in this study, is an adapted combination of the afore mentioned two models, and the models developed in Lecklin et al. (2011) and Rahikainen et al. (2017). The important hierarchical structures of the different models are illustrated with directed acyclic graphs (DAG) (e.g., Gelman et al 2014) and graphical maps, in which blue ellipses represent parameters, blue rectangles observations and green rectangles covariates. Yellow colored shapes are used to highlight certain parts of the models, which are currently being reviewed in the text. Relevant mathematical equations are written out in simplified form.

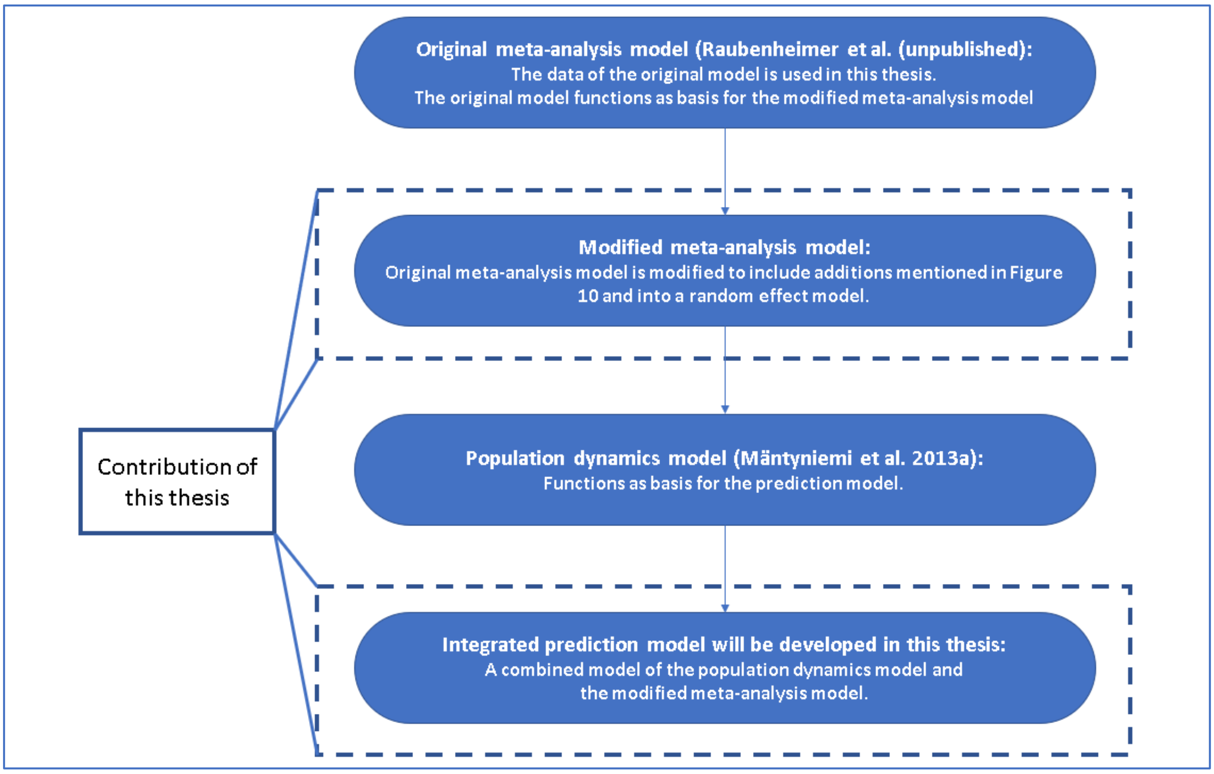


Figure 11, Outline of the models- section of materials and methods

3.1.1 Original meta-analysis model in Raubenheimer et al. (unpublished)

Raubenheimer et al. (unpublished) conducted a hierarchical Bayesian meta-analysis on mortality of herring eggs as a function of initial TPAH concentration in water from different oil types, and exposure time of herring eggs to PAH compounds. Data for the analysis was collected from laboratory studies. The collected data had a column for total mortality as a proportion, initial concentration of TPAH, exposure time in days and oil type (Appendix 1). Some of the results were controls, which were excluded from the analysis. A BHM was fitted to the data (Figure 12).

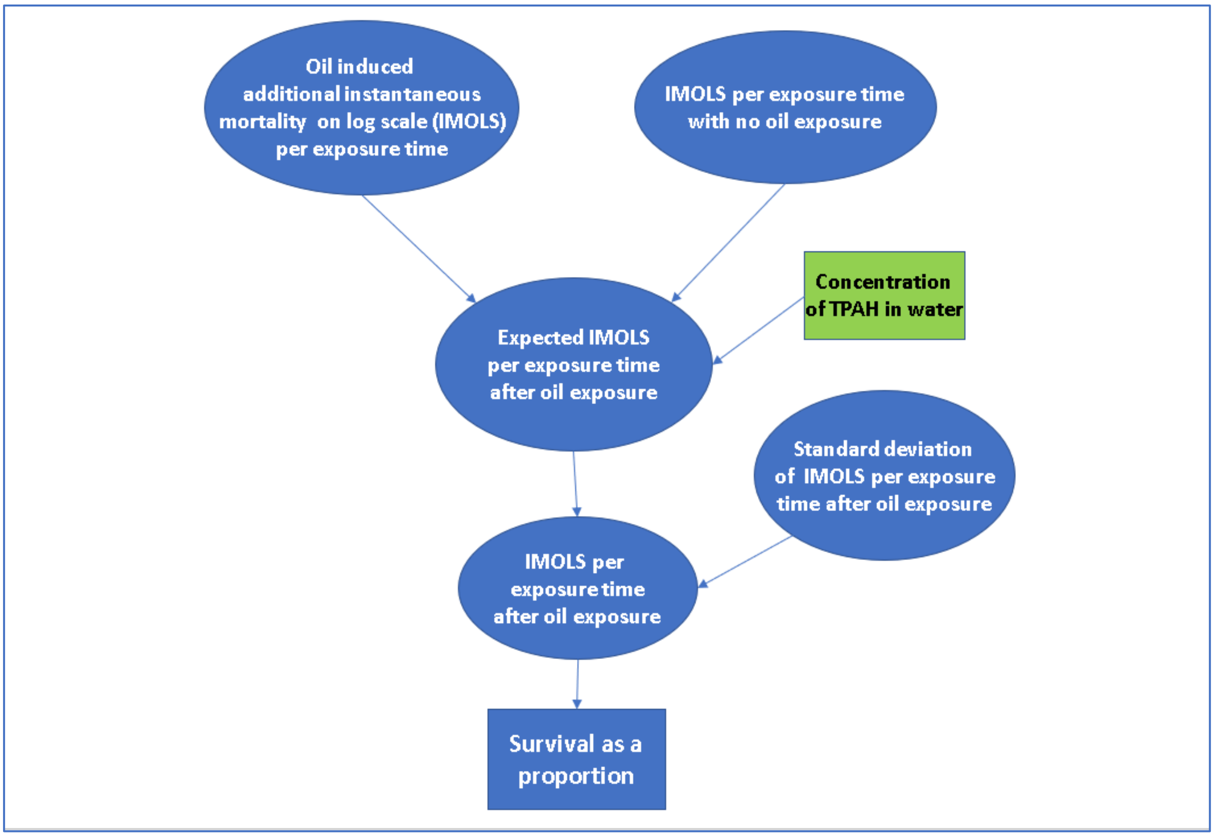


Figure 12, Original meta-analysis model in Raubenheimer et al. (unpublished)

The mortality as a proportion data was transformed first to survival as a proportion by subtracting it from one, and then to instantaneous mortality on logarithmic scale (IMOLS) per exposure time (1). IMOLS per exposure time after oil exposure, was modelled with a log Gaussian regression observation model (2, 3). The intercept parameter of the expected IMOLS per exposure time after oil exposure (3), was determined to be IMOLS per exposure time with no oil exposure. The slope parameter was determined to be oil induced additional IMOLS per exposure time. The slope parameter value determines the increase in expected IMOLS per exposure time after oil exposure, per increase of one unit in concentration on logarithmic scale. IMOLS per exposure time after oil exposure can be transformed back into original scale to get survival as a proportion (4).

$$\begin{matrix} \mathit{Instantaneous\ mortality} \\ \mathit{on}\ \log \mathit{scale}\ \ (\mathit{IMOLS}) \\ \mathit{per\ exposure\ time} \\ \mathit{after\ oil\ exposure} \end{matrix} = \log\left(\frac{-\mathit{log}\ \ (\mathit{Survival\ as\ a\ proportion\ data})}{\mathit{Exposure\ tima\ data}}\right) \qquad (1)$$

$$\begin{matrix} \mathit{IMOLS\ per\ exposure\ time} \\ \mathit{after\ oil\ exposure} \end{matrix} = N\left(\begin{matrix} \mathit{Expected\ IMOLS} \\ \mathit{per\ exposure\ time} \\ \mathit{after\ oil\ exposure} \end{matrix}, \begin{matrix} \mathit{Standard\ deviation} \\ \mathit{of\ IMOLS\ per\ exposure\ time} \\ \mathit{after\ oil\ exposure} \end{matrix}\right) \qquad (2)$$

$$\begin{matrix} Expected\ IMOLS \\ per\ exposure\ time \\ after\ oil\ exposure \end{matrix} = \begin{matrix} IMOLS\ per \\ exposure\ time \\ with\ no\ exposure \end{matrix} + \begin{matrix} Oil\ induced \\ additional \\ IMOLS \\ per\ exposure\ time \end{matrix} \times \log\begin{pmatrix} Concentration \\ of\ TPAH\ in \\ water\ data \end{pmatrix} \quad (3)$$

$$\begin{matrix} Survival\ as \\ a\ proportion \end{matrix} = \exp\left(-exp\begin{pmatrix} IMOLS \\ per\ exposure\ time \\ after\ oil\ exposure \end{pmatrix} \times Exposure\ time\ data \right) \quad (4)$$

3.1.2 Modified version of the original meta-analysis model developed in this thesis

For this thesis, the original meta-analysis model of Raubenheimer et al. (unpublished) is modified (Figure 13). The data is still the same as in the original model and transformed the same way as before. The observation model is still a log Gaussian regression model.

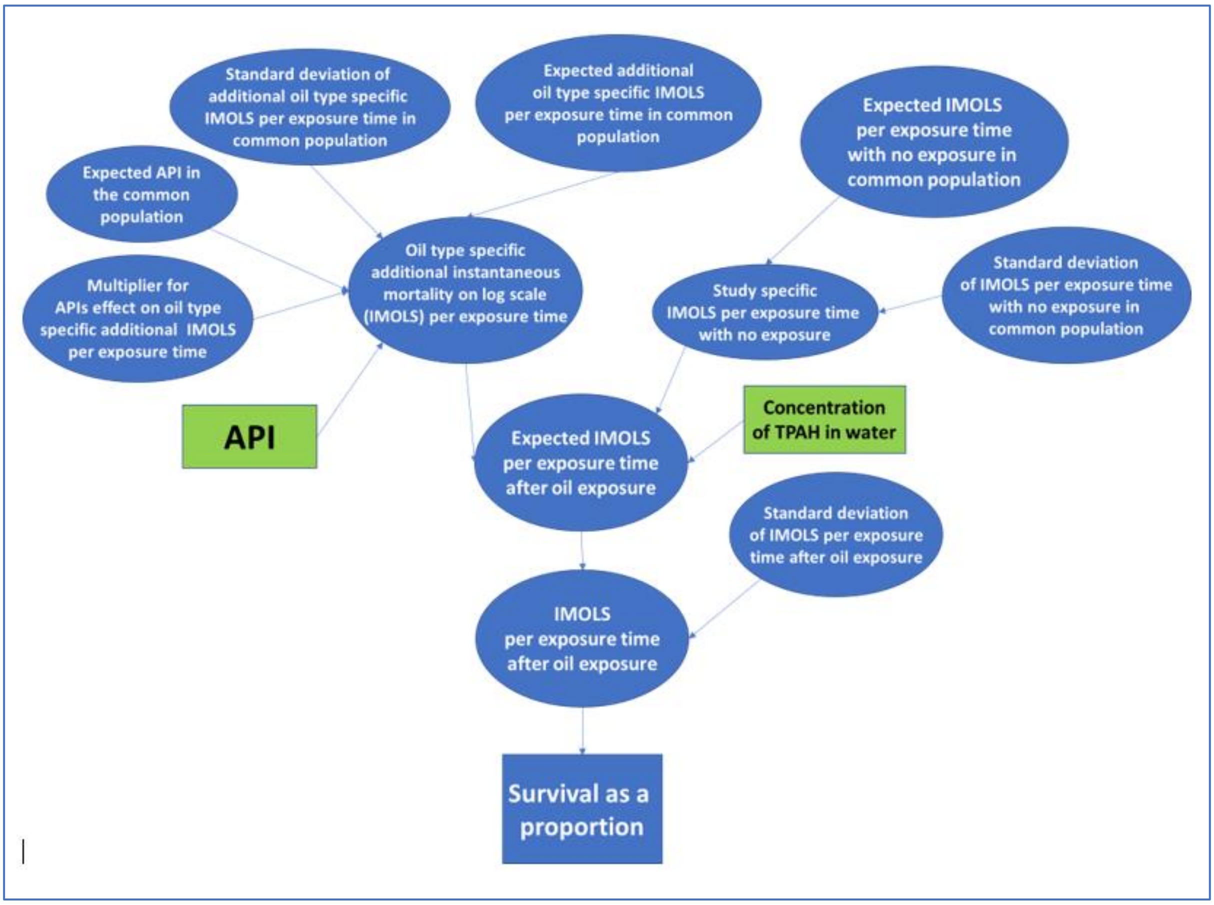


Figure 13, DAG of modified meta-analysis BHM

In the original model, oil induced additional instantaneous mortality on log scale (IMOLS) per exposure time was estimated for three oil type categories. Since oil types have very varying PAH compositions, all oil types in Raubenheimer et al.'s (unpublished) data are analyzed separately in this thesis. This is done by treating oil induced additional IMOLS per exposure time, as a normally distributed random effect varying by oil type. Oil type specific additional IMOLS per exposure time is conditional on expected value and standard deviation of oil induced additional IMOLS per exposure time in the common population. Common population is assumed to consist of theoretically infinite number of groups of different types of oil. In this thesis, these groups are assumed to consist of oils that have similar mortality causing characteristics, and the most important characteristic is assumed to be API. Individual oil's API affects additional mortality through its difference compared to expected API of all groups on average in the common population, multiplied by an API effect parameter (5).

$$\begin{matrix} \textit{Oil type specific} \\ \textit{additional IMOLS} \\ \textit{per exposure time} \end{matrix} = N\left(\begin{matrix} \textit{Expected additional} \\ \textit{IMOLS per exp. time in} \\ \textit{common population} \end{matrix} + \left(\begin{matrix} \textit{Individual oil's} \\ \textit{API covariate} \end{matrix} - \begin{matrix} \textit{Expected API} \\ \textit{in common} \\ \textit{population} \end{matrix}\right) \times \begin{matrix} \textit{Multiplier for} \\ \textit{API's effect} \end{matrix}, \begin{matrix} \textit{Standard deviation} \\ \textit{of additional mortality} \\ \textit{in common population} \end{matrix}\right) \quad (5)$$

IMOLS per exposure time with no exposure was treated as a fixed effect in the original model. Because the data in Raubenheimer et al. (unpublished) included laboratory studies with varying control experiment mortalities, mortality with no exposure is treated as a normally distributed random effect varying across different studies in the data set.

Modelling of the expected IMOLS per exposure time after oil exposure, was modified to be linearly separable (6). This makes it possible to use oil type specific additional IMOLS individually in the prediction model, where mortality without oil exposure is already considered.

$$\begin{matrix} \textit{Expected IMOLS} \\ \textit{per exposure time} \\ \textit{after oil exposure} \end{matrix} = \log\left(\exp\begin{pmatrix} \textit{Study specific IMOLS} \\ \textit{per exposure time} \\ \textit{with no exposure} \end{pmatrix} + \exp\begin{pmatrix} \textit{Oil type specific} \\ \textit{additional IMOLS} \\ \textit{per exposure time} \end{pmatrix} \times \log\begin{pmatrix} \textit{Concentration of} \\ \textit{TPAH in water} \\ \textit{data} \end{pmatrix}\right) \quad (6)$$

The oil induced mortality as a proportion results of Rahikainen et al. (2017), are used as one additional source of data for posterior estimation, and for estimating aspects of the Antonio Gramsci 1987 oil spill. The results of Rahikainen et al. (2017), did not include data for concentration, exposure time or specific oil type, and they could not be found from other literature either. Nissinen (2000) stated that the type of the oil was generally crude oil, but its origin or weight expressed as API is not known. For this data point, the model is modified to include exposure time and concentration as unknown parameters (Figure 14).

This data point is used to analyze probabilities of the Raubenheimer et al.'s (unpublished) data set's crude oils being the spilled oil in Antonio Gramsci 1987 spill. The analysis is done using BMA for the expected oil type specific additional IMOLS regression model, for each oil separately (7). The results of Rahikainen et al. (2017) were reported as additional mortality as a proportion and therefore, the parameter for IMOLS without exposure is dropped out, which is possible with the linearly separable model. This form of the equation will be used in the prediction model as well because the population model, which will be the basis of the prediction model, already considers mortality with no exposure.

$$\begin{matrix} Expected \\ additional\ oil \\ induced\ IMOLS \end{matrix} = \log\left(\left(\exp\begin{pmatrix} Oil\ type\ specific \\ additional\ IMOLS \\ per\ exposure\ time \end{pmatrix} \times \log\begin{pmatrix} Concentration\ of \\ TPAH\ in\ water \end{pmatrix}\right) \times \begin{matrix} Exposure \\ time\ of\ eggs\ to\ TPAH \end{matrix}\right) \quad (7)$$

To make it possible to estimate the parameter values of the Rahikainen et al. (2017) data point, a simulated data set was derived from the results of Rahikainen et al. (2017). Rahikainen et al. (2017) estimated the additional mortality as a proportion, on to a probability distribution with median of 17 % and a posterior 95 % probability interval from close to 0 % to 57 % mortality (Figure 15). The simulated dataset was approximated with a beta distribution by trial and error. The resulting distribution of the simulated data resembled the posterior distribution estimated by Rahikainen et al. (2017). The simulated data was assumed to be the result of a binomial experiment (observation model), with Beta (1,1) uniform prior distribution. The code of the modified meta-analysis model can be found in Appendix 2.

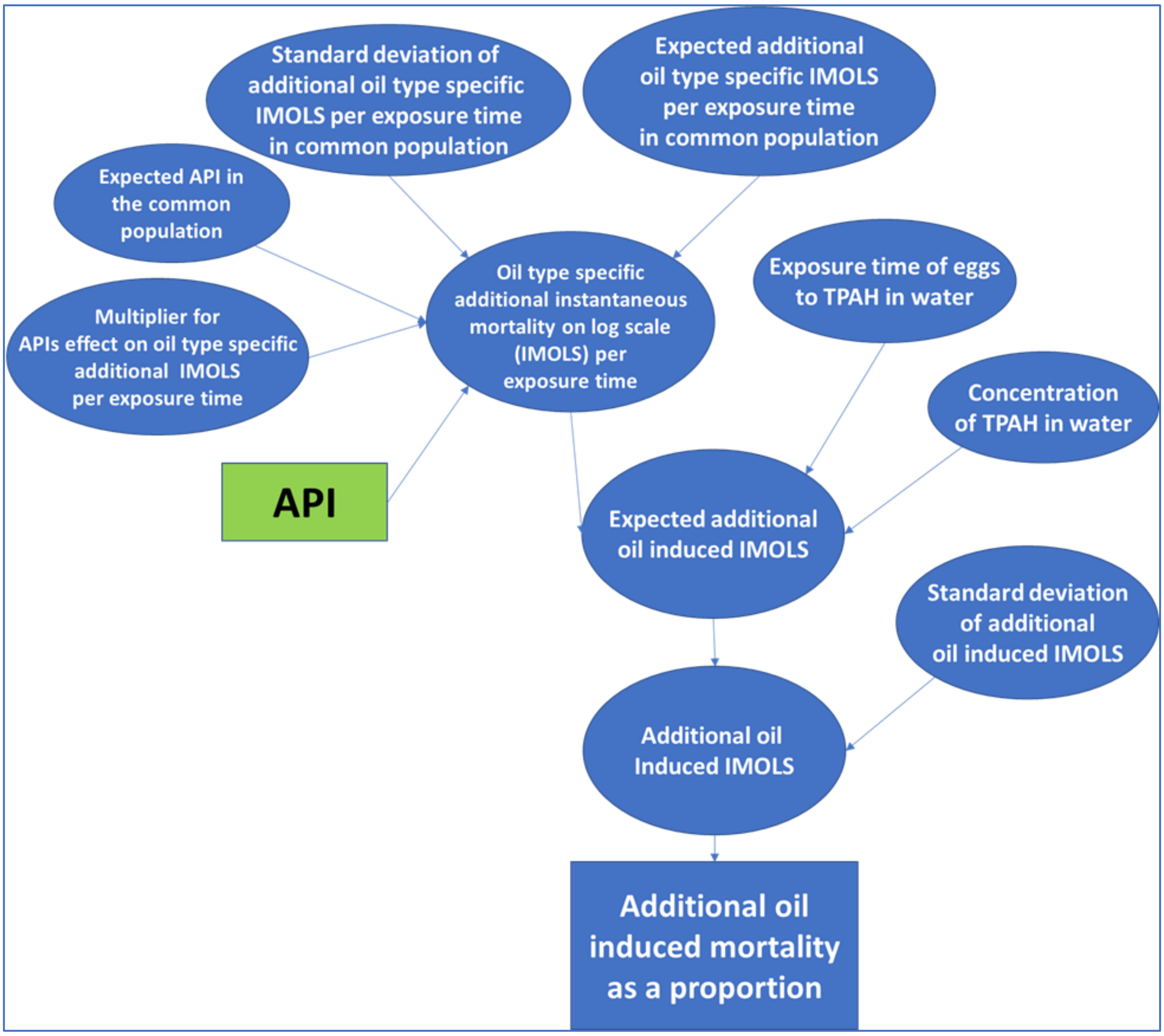


Figure 14, Meta-analysis model for Rahikainen et al. (2017) data point and the prediction model

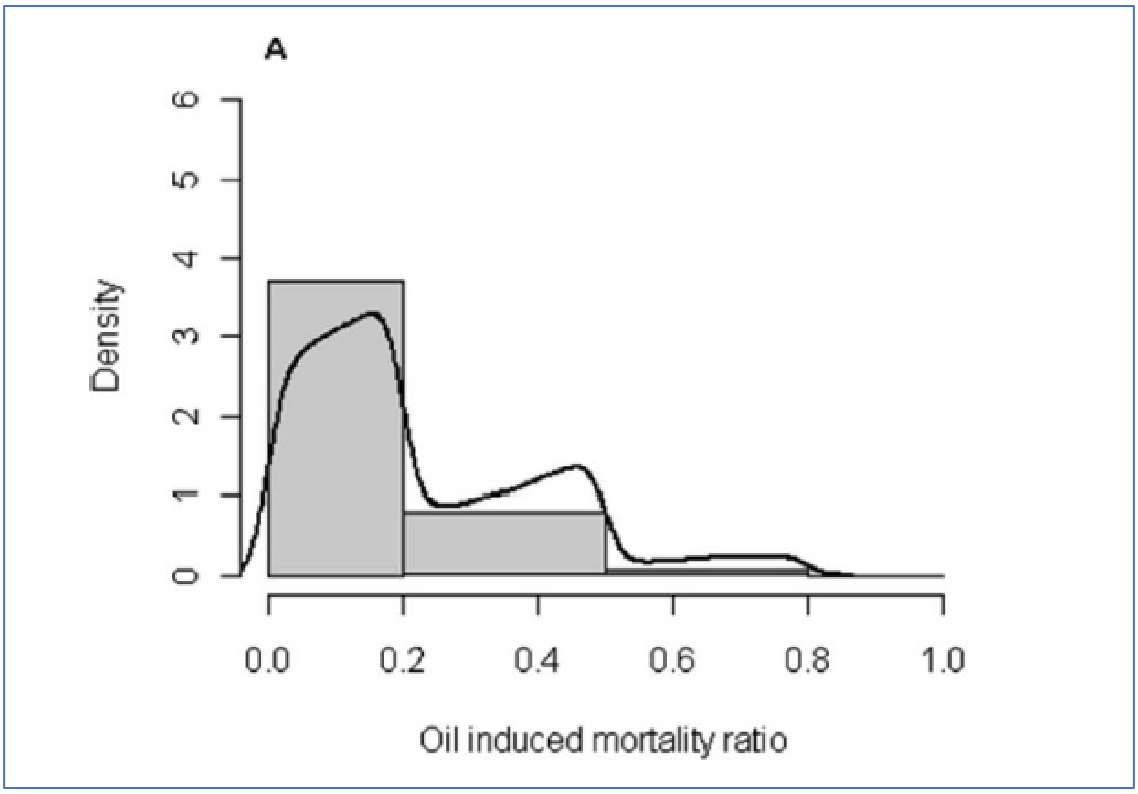


Figure 15, Posterior distribution of Antonio Gramsci 1987 spill mortality of herring offspring (black line), (Rahikainen et al. 2017)

Predicting with the modified meta-analysis model

In this study, the meta-analysis model is used to predict oil induced additional mortality of herring eggs as a proportion, in the context of hypothetical oil spill scenarios. This additional egg mortality will be used in addition to natural mortality of eggs, to reduce the number of spawned eggs in the population model. Because the population model considers natural mortality of eggs, equation 7 will be used. The predicted oil induced additional IMOLS needs to be transformed back into original scale (8). This transformation gives the predicted value as predicted survival of eggs as a proportion after oil exposure, without considering natural mortality. Subtracting this from one gives the additional oil induced mortality as a proportion for the prediction model (9).

$$\begin{matrix} \text{Predicted survival after} \\ \text{oil exposure without natural mortality} \\ \text{as a proportion} \end{matrix} = \exp\left(-\,exp\begin{pmatrix} \text{Predicted oil induced} \\ \text{additional IMOLS} \end{pmatrix}\right) \tag{8}$$

$$\begin{matrix} \text{Predicted oil induced additional} \\ \text{mortality as a proportion} \end{matrix} = 1 - \begin{matrix} \text{Predicted survival after} \\ \text{oil exposure without natural mortality} \\ \text{as a proportion} \end{matrix} \tag{9}$$

3.1.3 Basis of the prediction model: Population model (Mäntyniemi et al. 2013a)

In this section, the population model developed by Mäntyniemi et al. (2013a) will be explained in relevant detail. This model is used as the basis for the prediction model developed in this thesis. The population model will be run in its original form to estimate population dynamics parameter posteriors. The modified meta-analysis model will be run separately for estimating posteriors, which will be integrated into the population dynamics model for prediction.

Data for the population model

The original data in the population model is from data sets used by ICES Baltic Fisheries Assessment Working Group (WGBFAS) for Baltic Sea main basin herring. The data set includes age-specific commercial catches, mean weights-at-age from years y = 1974 – 2007, and acoustic survey estimates from years y = 1982 - 2007.

General structure of the population model

The population model is a generic hierarchical state-space population dynamics model. It models the full life cycle of the Baltic Sea main basin herring. The model is fully age-structured with age classes A = 1 – 8, and many of the parameters are modelled as stochastic and weight dependent including natural mortality, fecundity, and fishery selection. The model loops through all observation years and all age classes for those parameters that are age class specific. There are several age distribution parameters to which the age specific parameters are hierarchically dependent to. Figure 16 illustrates the three key parameter groups in a simplified form due to the model's complex structure. The three key parameter groups were decided based on information received from stakeholders regarding herring population dynamics (Mäntyniemi et al., 2013b). The same expert elicitation results were also used for prior specification.

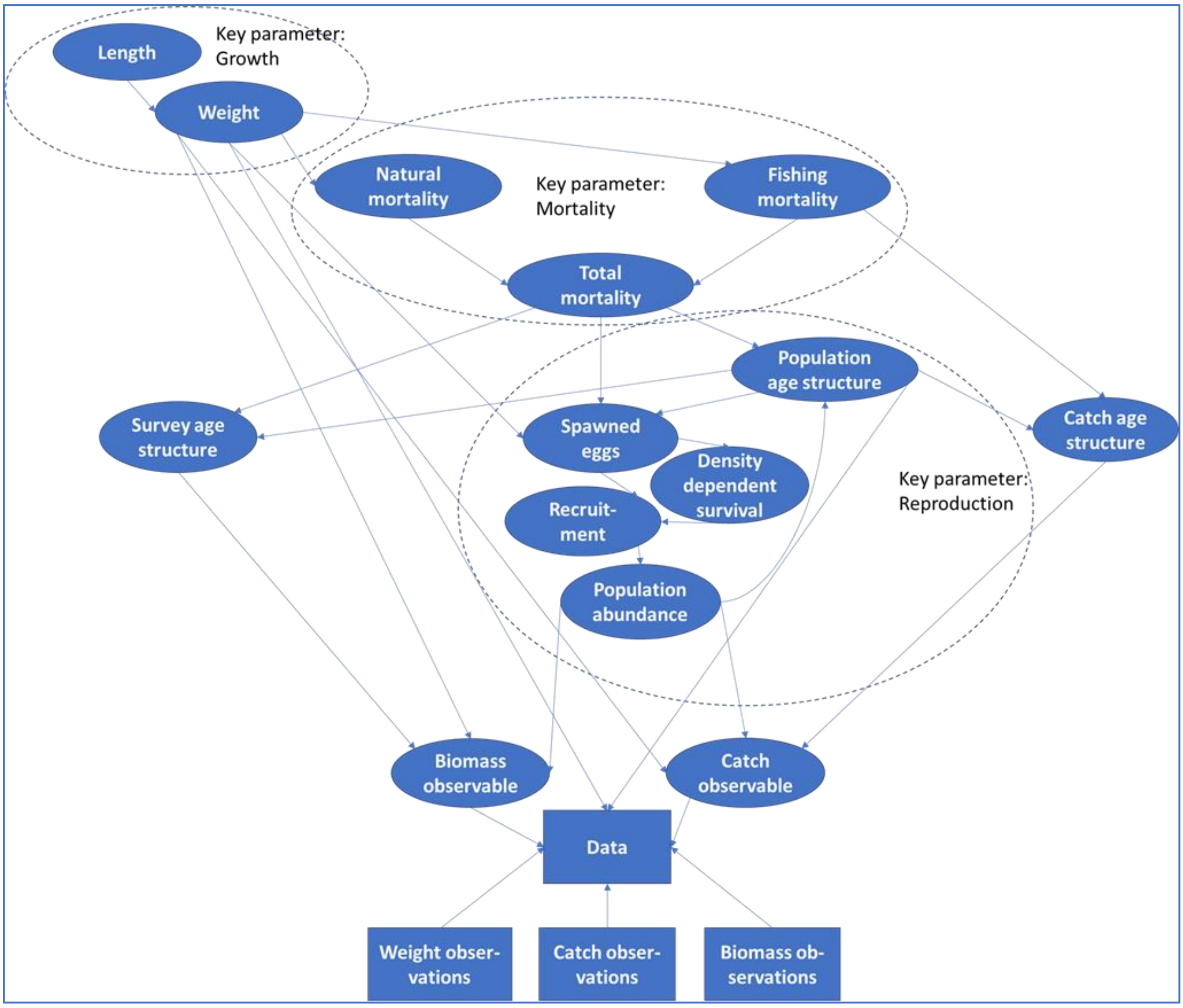


Figure 16, Simplified DAG of the population model

3.1.4 Prediction model developed in this thesis.

In this section, the methodology will be explained regarding how the modified meta-analysis model and the population model are integrated to form the prediction model. The methodology, of how the prediction model developed in this thesis will be used for prediction, will be explained as well.

Relevant population model parameters and equations for the integration of the meta-analysis model

The modified meta-analysis model posteriors are integrated into the population dynamics model using a similar methodology as in Rahikainen et al. (2017). They included a parameter for additional mortality of herring offspring to the calculation of recruits in the population model in the year of the oil accident of Antonio Gramsci 1987 (10, 11).

$$\log(Recruitment_{no\ exposure}) \sim N\left(\log\left(\begin{matrix}Number\ of\\spawned\ eggs\end{matrix} \times \begin{matrix}Density\ dependent\\survival\ of\ eggs\end{matrix}\right) - 0.5 \times \sigma\ ,\ \sigma\right) \tag{10}$$

$$Recruitment_{after\ oil\ exposure} = Recruitment_{\ no\ exposure} \times \left(1 - \begin{matrix}Oil\ induced\ mortality\ of\\herring\ offspring\end{matrix}\right) \tag{11}$$

, where σ is residual variance of recruitment process. In the predictions of this study, the modified meta-analysis model is used to predict additional mortality of herring eggs as a proportion. To model oil impact on eggs alone instead of total offspring, the additional mortality needs to be included in the calculation of spawned eggs in the year of the accident, to get survived spawned eggs after oil exposure (Figure 17). This comes from the idea that density dependent survival of eggs to recruits happens after the more short-term effect of oil induced additional mortality.

In the population model, the density dependent survival of eggs is assumed to follow either Beverton-Holt or Ricker models. These models assume a density dependent survival of young fish to recruits (Beverton and Holt, 1959; Ricker, 1954). In the population model, recruitment is calculated from survived eggs (10), and the stock recruitment models are thus parameterized in terms of density dependent survival of eggs. This means density dependent survival is limited to egg phase. As stock abundance increases, and consequently the number of spawned eggs, the density dependent survival of eggs decreases recruitment exponentially and vice versa. The posterior probabilities of the two models in the population model were 93 percent for Ricker model and 7 percent for Beverton-Holt. Therefore, this study focuses only on the effects of the Ricker model.

Parameter for proportion of oiled coastline, in herring spawning areas, needs to be added for integrating the modified meta-analysis posteriors, and prediction of oil impacts. The effect of additional oil induced mortality of eggs is calculated as spawned eggs survived after exposure (12). Eggs survived after oil exposure is then simply added to the calculation of recruits (13), to integrate the oil impact to population dynamics.

$$\begin{matrix}Eggs\ survived\\after\ oil\ exposure\end{matrix} = \begin{matrix}Number\ of\\eggs\ spawned\end{matrix} \times \left(1 - \begin{matrix}Additional\ oil\ induced\\mortality\ of\ herring\ eggs\end{matrix} \times \begin{matrix}Proportion\ of\\oiled\ coastline\end{matrix}\right) \tag{12}$$

$$\log(Recruitment) \sim N\left(\log\left(\begin{matrix}Eggs\ survived\\after\ oil\ exposure\end{matrix} \times \begin{matrix}Density\ dependent\\survival\ of\ eggs\end{matrix}\right) - 0.5 \times \sigma\ ,\ \sigma\right) \tag{13}$$

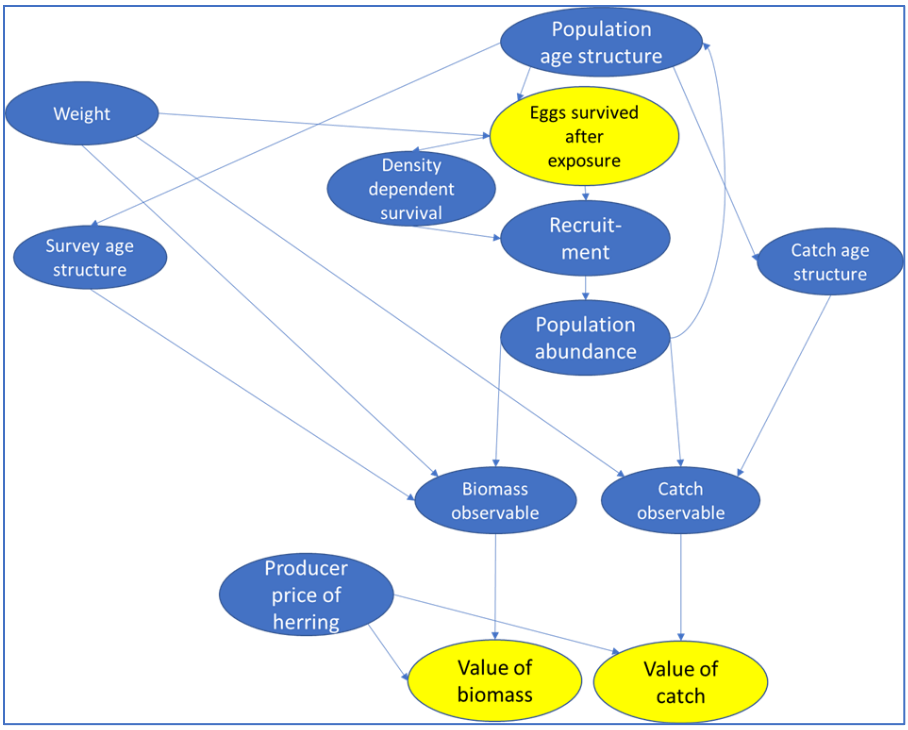


Figure 17, DAG of the integration of the oil impact into the population model

Prediction of the economic values of catches and total biomass

To enable the prediction of economic values of catch and biomass, a parameter for annual first sale price of herring is added to the model. Values are calculated by multiplying catch and biomass observables of the population model (14 – 17) with the first sale price. The observable parameters estimate the true weights of catch and biomass.

$$\begin{matrix} Biomass \\ observable \end{matrix} = \begin{matrix} Population \\ abundance \end{matrix} \times \sum_{a=1}^{A} \begin{matrix} Mean\ weight \\ of\ age\ class \end{matrix} \times \begin{matrix} Proportion\ of\ each \\ age\ class\ in\ survey\ data \end{matrix} \tag{14}$$

$$\begin{matrix} Catch \\ observable \end{matrix} = \begin{matrix} Population \\ abundance \end{matrix} \times \begin{matrix} Probability\ a \\ fish\ gets\ caught \end{matrix} \sum_{a=1}^{A} \begin{matrix} Mean\ weight \\ of\ age\ class \end{matrix} \times \begin{matrix} Proportion\ of\ each \\ age\ class\ in\ catch\ data \end{matrix} \tag{15}$$

$$\begin{matrix} Value\ of \\ biomass \end{matrix} = \begin{matrix} Biomass \\ observable \end{matrix} \times \begin{matrix} First\ sale\ price \\ of\ herring \end{matrix} \tag{16}$$

$$\begin{matrix} Value\ of \\ catch \end{matrix} = \begin{matrix} Catch \\ observable \end{matrix} \times \begin{matrix} First\ sale\ price \\ of\ herring \end{matrix} \tag{17}$$

Predicting with the integrated prediction model developed in this thesis

The idea of this study is to use the integrated bioeconomic model, consisting of the population model developed by Mäntyniemi et al. (2013a) and the modified meta-analysis model developed in this thesis, for predicting the impacts of hypothetical oil spills on Baltic Sea main basin herring population, and the consequential economic impacts to fishermen. The posteriors of the population model and the modified meta-analysis model are used to predict future parameter values from the posterior predictive distribution (Figure 18). The modified meta-analysis model posteriors are programmed into a separate block (Appendix 3) inside the population model, for the purpose of predicting the additional mortality caused by the oil accident in each scenario.

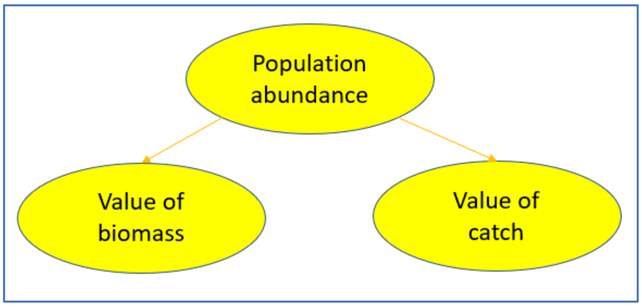


Figure 18, Predicted quantities

3.2 Running of the models and prior specification

Modified meta-analysis model run for estimating parameter posteriors

The modified meta-analysis model is first run separately to estimate the parameter posteriors that will be integrated into the population model, and for estimating certain aspects of Antonio Gramsci 1987 spill. Table 3 presents the specified priors for the modified meta-analysis model.

Hyperparameters	Distribution	Truncation
API effect	*N (0, 1)*	
Expected API in the common population	*N (32.7, 15)*	
Expected oil type specific additional IMOLS per exposure time in common population	*N (0, 10)*	
Standard deviation of oil type specific additional IMOLS per exposure time in common population	*U (0.01, 50)*	
Standard deviation of IMOLS per exposure time with no exposure in common population	*U (0.01, 10)*	
Expected IMOLS per exposure time with no exposure in common population	*N (0, 10)*	
Standard deviation of IMOLS per exposure time after oil exposure/Standard deviation of additional oil induced IMOLS	*U (0.01, 10)*	
Concentration of TPAH in water for Rahikainen et al. data point	*N (0.006, 0.04)*	*> 0*
Exposure time in days for Rahikainen et al. data point	*N (15, 4)*	*> 0*
Probabilities of different models in BMA for Rahikainen et al. data point	*Equally likely*	

Table 3, Priors for the modified meta-analysis model run

Prior for the expected API in the common population was specified according to the OPEC reference basket concept (OPEC, 2021). In the basket are the API figures of the main exported crude oils of OPEC member countries, weighted by production and export amounts to main markets. The weighted average API of the basket is 32,7, which is used as the mean of the prior. Standard deviation is set to a high enough value to represent uncertainty in prior knowledge, and high variation in oil type characteristics between the common population groups. The prior for API effect is specified as a vaguely informative normal distribution. API effect values are assumed to lie between -1 and 1.

There were 8 different oil products in the experiment studies used in Raubenheimer et al.'s (unpublished) data. According to Blasko et al. (1972), different crude oils from Cook Inlet have an average API gravity of 35,11. Venezuela crude oil and Tuimaza crude oil used in Linden (1978) had 31,14 and 33 API gravities. Benzene has 32,7 API gravity (Stauffer et al., 2008). According to EIA (2020), no. 1 fuel oil, a light fuel oil, has about 43 API gravity. According to ITOPF (2002), Cosco Busan heavy fuel oil has 11-15 API, and ANSCO has 28 API gravity. According to Banet (1994), Prudhoe Bay crude oils usually have 25–30 API gravities. These API figures are used as the API covariates in equation 5.

Expected IMOLS per exposure time with no exposure in common population, was specified a noninformative normal prior. This reflects the varying natural mortalities in nature (Table 2) and varying natural mortalities in the studies of Raubenheimer et al.'s (unpublished) data set. Prior for the expected oil type specific additional IMOLS per exposure time in common population, was specified as noninformative normal, reflecting the large variation in oil characteristics between different possible groups. The priors for all standard deviation hyperparameters are specified as uninformative uniform distributions.

Prior for exposure time for the Rahikainen et al. (2017) data point, is specified according to 15 days expected incubation time and timing of the Antonio Gramsci accident. The spill occurred February 1987 in ice covered waters and the oil remained under the ice for two months (Urho, 1991). The low water temperature, ice coverage, and possible general oil type being crude oil, suggest the weathering of PAH compounds was slow (Wiens 2013; Fingas et al. 2011; National research council 2003). Therefore, the exposure time of herring eggs could have been close to, or equal to incubation time. In cold water, incubation time can be even as high as 40 days (Bigelow and Schroeder, 1953), which was considered in the standard deviation of the prior. The toxic PAH compounds were assumed to have persisted in the water column under the ice until spawning time, and throughout the incubation time. Since there are no mentions in literature of measured TPAH concentrations in the water column after the spill, the prior for concentration was estimated according to concentrations of other known spills. The prior mean was specified to correspond the average concentration (in parts per million (ppm)) of the range reported by Wolfe et al. (1994) after the Exxon Valdez spill. The standard deviation of the prior was specified broad enough to allow other realistic values, considering the spill volume and the oil type being generally crude oil. The different oil type specific BMA models for expected additional mortality, were considered equally likely a priori.

Prediction model runs of the hypothetical oil spills

The population model is run in its original form for estimating posteriors of its parameters from the historical observed data used in Mäntyniemi et al. (2013a). These posteriors are used in the prediction model scenario runs. Of the modified meta-analysis model posteriors, only estimated oil type specific additional IMOLS per exposure time parameters and standard deviation of additional oil induced IMOLS parameter are transferred to the prediction model (Figure 19).

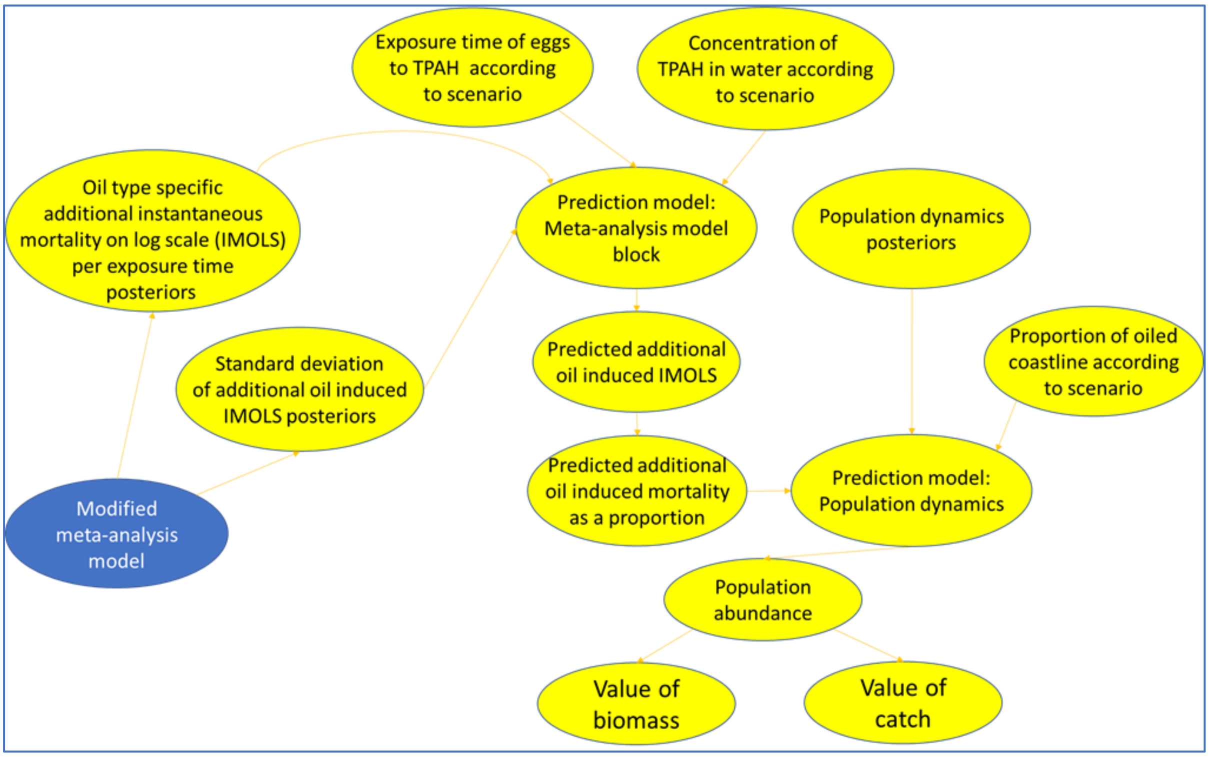


Figure 19, Transferring posteriors to the prediction model

The scenarios run with the prediction model vary across four parameters (Figure 20). There are in total 36 scenario combinations. Initial population abundance will be set to two different levels. Both levels will be run with two different oil types. Each oil type will cover three different proportions of oiled herring spawning coastline, with three different concentrations of TPAH in water. The assumption is that in the case of an accident, samples and information for these parameters would have been collected and calculated. Making accurate predictions is always dependent on the information content of field samples (Boehm et al. 2013). Concentration parameter is assigned informative normal priors, with expected values according to the scenarios, and concentrations of scenario oils found in past spills (Table 2). The model assumes the hypothetical spills have happened right before spawning, so exposure time will also be specified an informative normal prior with expected value of 15 days, corresponding the probable water temperatures during spring spawning, with deviation high enough to allow longer incubation time in colder waters. The oiled coastline parameter is specified an informative beta prior varying according to the scenarios. The population abundance levels are set to the corresponding posterior years from the population model run posteriors. The years are chosen to represent different levels of stock-recruitment ratios to induce effects according to the Ricker model parameterization in Mäntyniemi et al. (2013a). The last estimated year of the population model is on the level where stock abundance is on a relatively high level, according to the Ricker model, so number of spawned eggs is high. When number of spawned eggs is high, density dependent survival of eggs is low and so is recruitment. The lowest estimated year on the other hand is on a level, where number of spawned eggs is small, so density dependent survival and recruitment are high.

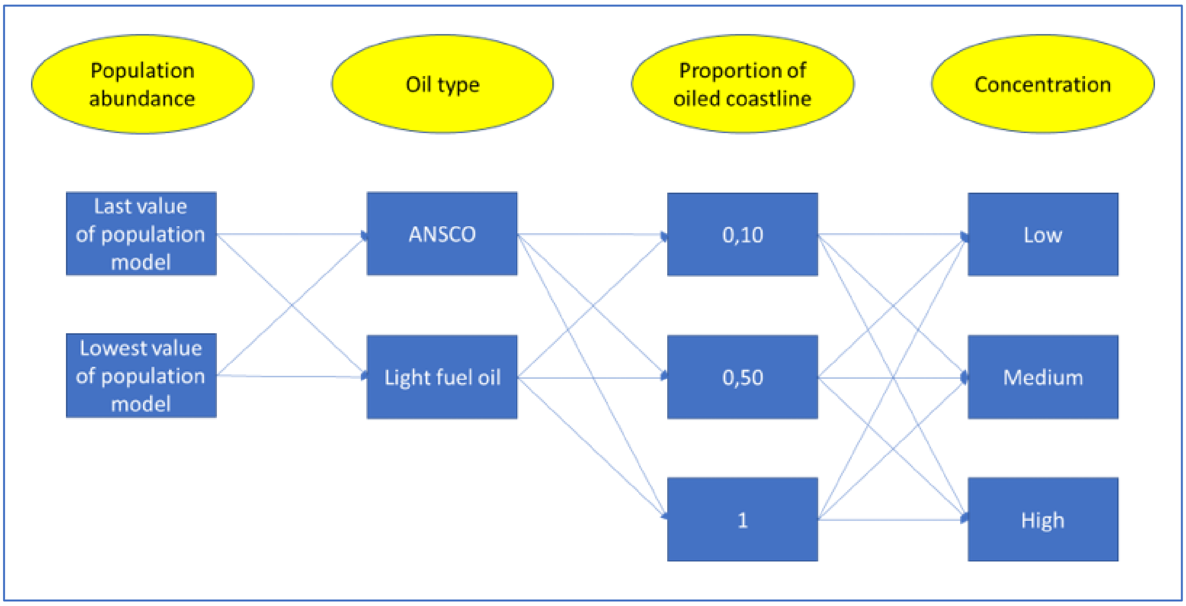


Figure 20, Illustration of the scenario combinations

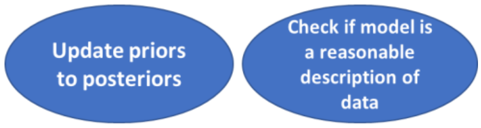
3.3 Computation and model checking

The posteriors of the model parameters were estimated using MCMC sampling from the joint posterior distribution. The simulation was implemented using Just Another Gibbs Sampler (JAGS) built on top of R programming language.

In all the MCMC runs, four independent MCMC chains were ran on separate processors. For the meta-analysis model run, 100 000 samples were generated for each chain. For the population model run, 5 000 000 samples were generated for each chain, saving every 100th sample. The predictions were made generating 100 000 samples for each chain, saving every 10th sample. The prediction runs took approximately 1.5 weeks. The population model run took approximately 1 week. These computation times highlight the demanding computational requirements of the kind of modelling done in this thesis.

The non-convergence of the modified meta-analysis model chains was examined, first visually by plotting the trace plots of the parameter chains, and then running Gelman-Rubin diagnostics. The model was checked with posterior predictive checks and plotting Bayesian p-values. The population model was run identically as in Mäntyniemi et al. (2013a) so no model checking was done for it in this thesis.

4 Results



4.1 Modified meta-analysis model run

In this section, the results from running the modified meta-analysis model described in section 3.1.2 are presented. The results of checking the modified meta-analysis model are presented as well. The results of the prediction model scenario runs are presented in the next section.

Posteriors of oil type specific additional instantaneous mortality on log scale (IMOLS) per exposure time parameters

As a reminder for reviewing the results, the common population is assumed to consist of theoretically infinite number of oil type groups. Oils belonging to a certain group have similar mortality causing characteristics. All the oils in the data set used in this thesis, are samples from different groups of the common population. The different common population parameters presented below, describe average expected values and standard deviations of the theoretically infinite number of groups.

The hyperparameters of additional oil type specific IMOLS per exposure time parameters, were not well known a priori. They were assigned uninformative uniform or vaguely informative normal priors (Table 3). Posteriors of the hyperparameters and parameters conditional on hyperparameters, are presented in Table 4. IMOLS values less negative mean more lethal oil and vice versa.

Hyperparameters	**Mean**		**SD**
API effect	*0,2396*		*0,1860*
Expected API in the common population	*35,7800*		*14,1514*
Expected oil type specific additional IMOLS per exposure time in common population	*-5,9118*		*3,7591*
Standard deviation of oil type specific additional IMOLS per exposure time in common population	*1,5602*		*1,8231*
Parameters	**Mean**	**API covariate**	**SD**
Additional IMOLS per exposure time of ANSCO	*-9,1434*	*28*	*2,5212*
Additional IMOLS per exposure time of Prudhoe Bay crude oil	*-7,7121*	*27*	*2,5277*
Additional IMOLS per exposure time of Venezuela crude oil	*-6,9203*	*31.4*	*1,2185*
Additional IMOLS per exposure time of Cook Inlet crude oil	*-6,1776*	*35*	*2,0072*
Additional IMOLS per exposure time of Tuimaza crude oil	*-6,6242*	*33*	*1,6462*
Additional IMOLS per exposure time of benzene	*-7,2972*	*32.7*	*2,3850*
Additional IMOLS per exposure time of heavy fuel oil	*-11,7502*	*13*	*4,4835*
Additional IMOLS per exposure time of light fuel oil	*-4,4518*	*43*	*0,4244*

Table 4, Posteriors of oil type specific additional mortality parameters

The API effect hyperparameter tells how much the expected value of oil type specific additional IMOLS per exposure time increases, or decreases, per unit of difference between oil type API covariate and expected API in the common population. The posterior's large standard deviation compared to its mean, reflects the uncertainty regarding the true value of the parameter. The uncertainty decreased significantly from prior to posterior (Figure 21). Expected API in the common population parameter did not changed much from prior to posterior (Figure 21). Since the prior was only vaguely informative, this reflects much variation in the common population and in the data, and/or that the posterior is mostly affected by the prior.

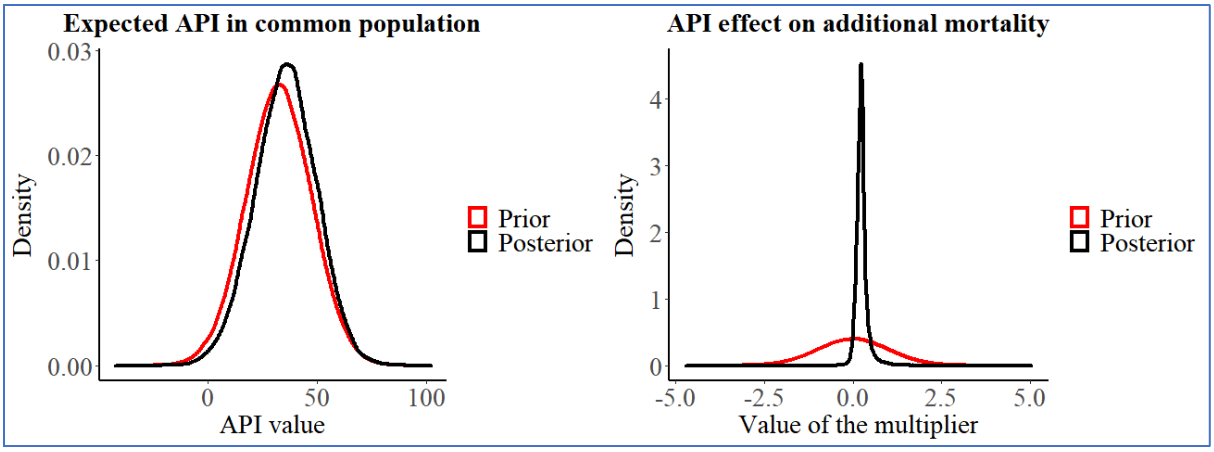


Figure 21, Posterior vs. prior of API effect and expected API in the common population

Expected oil type specific additional IMOLS per exposure time in common population parameter, represents the expected additional IMOLS per exposure time on average in all possible oil type groups in the common population. Since it was given a vaguely informative prior, the posterior was mostly affected by data (Figure 22). Posterior mean seems to lie somewhere between light fuel oil's mean and Cook Inlet crude oil's mean (Table 4). Standard deviation of the posterior tells the uncertainty regarding the true value of the parameter. The deviation has decreased significantly from prior to posterior, which is not surprising given the vagueness of the prior (Figure 22).

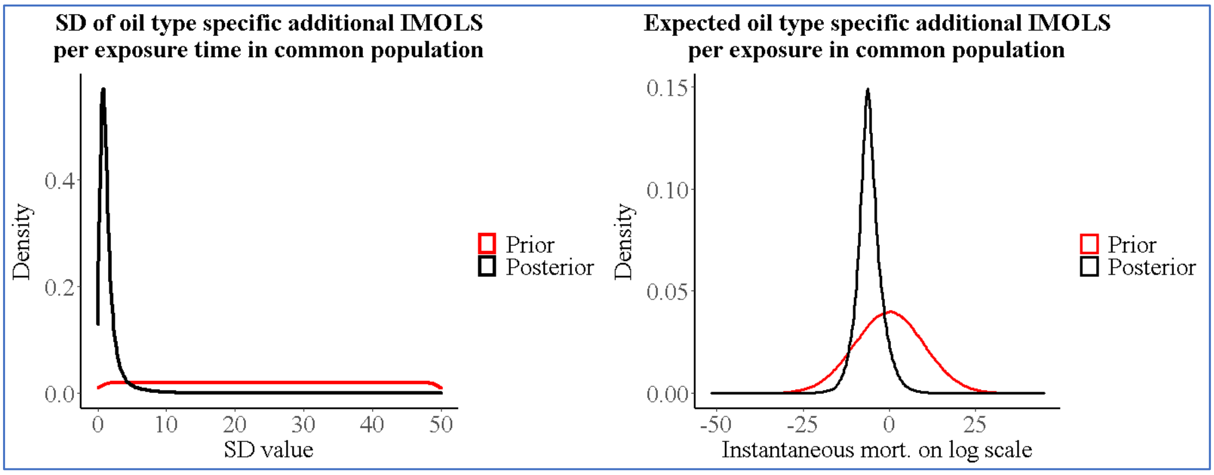


Figure 22, Posterior vs. prior of standard deviation and expected value of oil type specific additional IMOLS per exposure time in the common population

Standard deviation of oil type specific additional IMOLS per exposure time in common population parameter tells the expected deviation around the expected value within a group on average in the common population. The parameter has large standard deviation compared to its mean, representing uncertainty regarding the true value of this parameter. The expected value of this parameter affects the standard deviation of the expected oil type specific additional IMOLS per exposure time in common population parameter's standard deviation. If the expected value of the standard deviation parameter is high, then the standard deviation of the expected value parameter is high as well. Since the prior of this parameter was uniform, the posterior is only affected by the data.

Additional IMOLS per exposure time parameters of the oils in the data set, have somewhat similar standard deviations around their means proportionally, compared to the standard deviation parameter of the common population, except for light fuel oil. The standard deviations of these parameters represent uncertainty regarding the true values of the parameters. Therefore, uncertainty seems to be very low, proportional to the expected value, for light fuel oil compared to the rest of the oils.

According to the results, light fuel oil is most lethal and heavy fuel oil least lethal. Venezuela, Cook Inlet and Tuimaza crude oils seem to be somewhat equally lethal. ANSCO seems to be somewhere in between heavy fuel oil and Prudhoe bay crude oil. It is easier to understand the effect of these parameters, by using them in equation 4 with fixed concentration (0,1 ppm) and exposure time (15 days), then transforming the results with equation 5 and subtracting from one to get total additional mortality as a proportion (Figure 23).

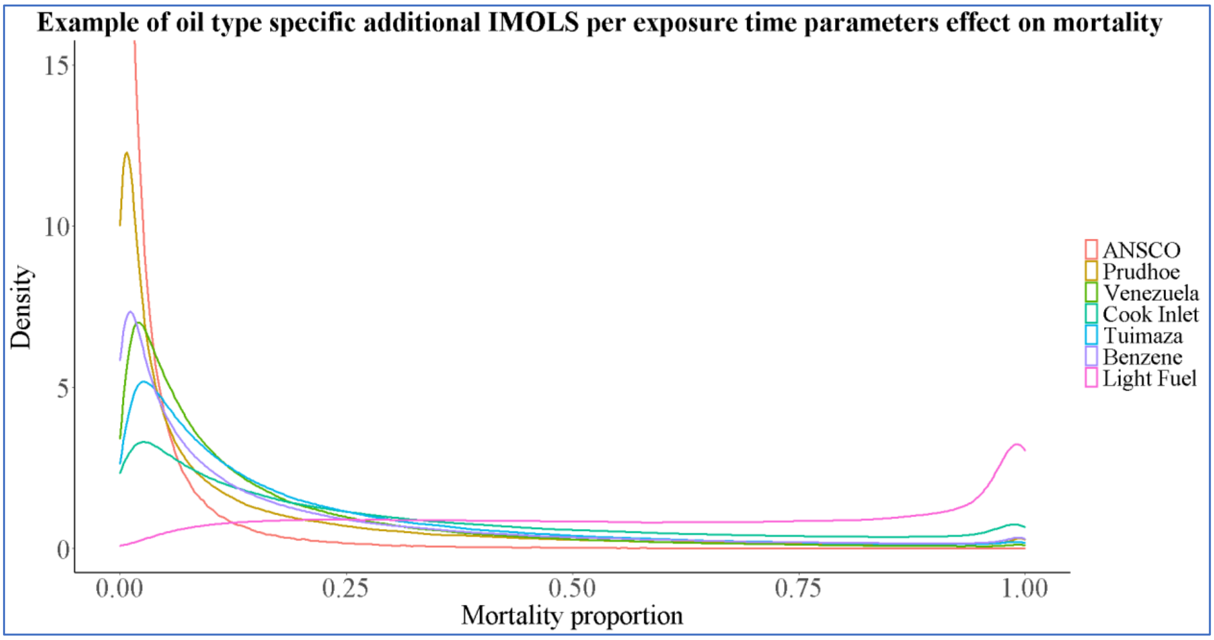


Figure 23, Example of oil type specific additional IMOLS per exposure time parameters' effect on total mortality as a proportion (concentration = 0,1 ppm, exposure time = 15 days)

Posteriors of IMOLS per exposure time with no oil exposure parameters

Even though parameters related to IMOLS per exposure time with no exposure are not transferred to the prediction model, their posteriors are analyzed to see how the idea of treating IMOLS per exposure time with no exposure as a random effect works. The hyperparameters were not well known a priori and were assigned uninformative uniform or vaguely informative normal priors (Table 3). Posteriors of the hyperparameters and of parameters conditional on hyperparameters are presented in Table 5.

Hyperparameters	**Mean**	**SD**
Standard deviation of IMOLS per exposure time with no exposure in common population	*2,1982*	*0,6252*
Expected IMOLS per exposure time with no exposure in common population	*-3,9353*	*0,7121*
Parameters	**Mean**	**SD**
IMOLS per exposure time with no exposure, study 1	*-3,7104*	*0,3944*
IMOLS per exposure time with no exposure, study 2	*-4,8312*	*0,4809*
IMOLS per exposure time with no exposure, study 3	*-5,0117*	*0,3720*
IMOLS per exposure time with no exposure, study 4	*-3,1468*	*0,4886*
IMOLS per exposure time with no exposure, study 5	*-5,6367*	*0,8279*
IMOLS per exposure time with no exposure, study 6	*-5,4436*	*0,8129*
IMOLS per exposure time with no exposure, study 7	*-5,2553*	*0,2732*
IMOLS per exposure time with no exposure, study 8	*-5,4163*	*0,5208*
IMOLS per exposure time with no exposure, study 9	*-2,8400*	*0,6794*
IMOLS per exposure time with no exposure, study 10	*0,4352*	*0,2796*
IMOLS per exposure time with no exposure, study 11	*-2,6562*	*0,6115*

Table 5, Posteriors related to mortality with no exposure

In this study, the parameters for IMOLS per exposure time with no exposure are treated as random effects varying across different studies in the data set. Assumption of the parameters' treatment as random effect was made, because of the varying natural mortalities in the data set studies. For example, study ten had large natural mortality, which is reflected in the expected value of its study specific IMOLS per exposure time with no exposure parameter. The standard deviations of the parameters are mostly small compared to their means, except for study ten, and they represent uncertainty regarding the true values of the parameters. Standard deviations of the common population hyperparameters have decreased significantly from prior to posterior (Figure 24). The priors were however uniform or vaguely informative normal, and thus posteriors are mostly or only affected by data.

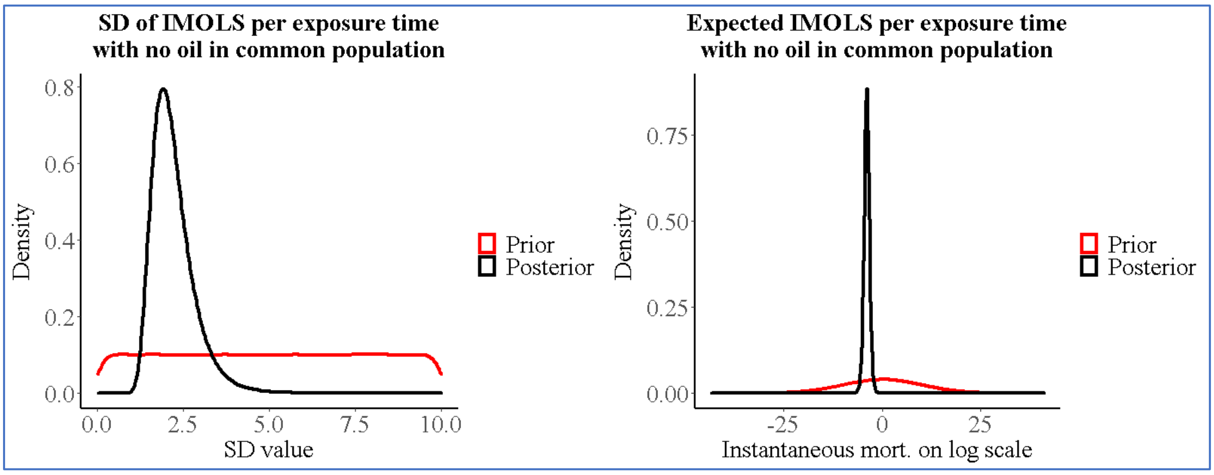


Figure 24, Prior vs. posterior of standard deviation and expected value of IMOLS per exposure time with no exposure in the common population

The effects of the study specific IMOLS per exposure time with no exposure parameters on mortality as a proportion are best illustrated with an example using fixed concentration (0,02 ppm), fixed oil type for additional mortality (Venezuela crude oil) and fixed exposure time (15 days) (Figure 25). Study ten is excluded from the example, because with such large natural mortality, total mortality as a proportion is always close to one in this example.

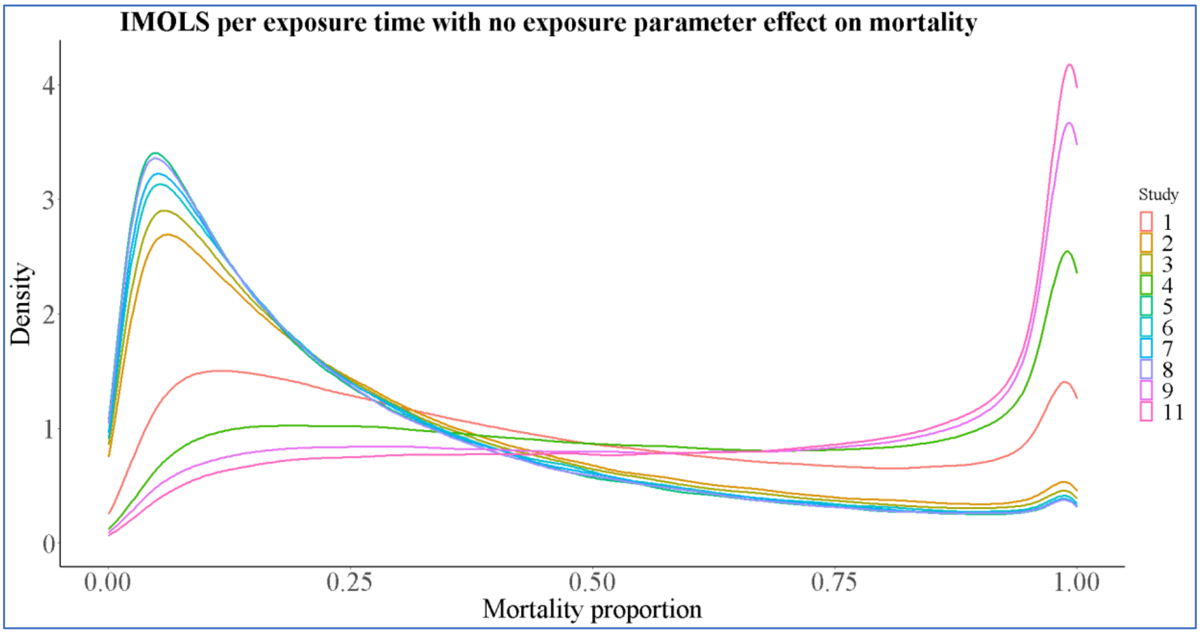


Figure 25, Example of the effect of study specific IMOLS per exposure time with no exposure parameters on mortality as a proportion (concentration = 0,02 ppm, exposure time = 15 days, oil type = Venezuela crude oil)

Estimating aspects of the Antonio Gramsci 1987 spill

Part of the purpose for running the modified meta-analysis model, was to estimate aspects of the Antonio Gramsci oil spill of 1987 (Figures 26). In the posterior, much probability has been allocated away from oil type one, ANSCO. It seems oil types three, Venezuela crude oil, four, Cook Inlet crude oil and five, Tuimaza crude oil, are the most probable crude oil types, from the data set's crude oils, to have been the oil type involved in the Antonio Gramsci 1987 spill. Oil type two, Prudhoe Bay crude oil, remained somewhat unchanged from prior to posterior.

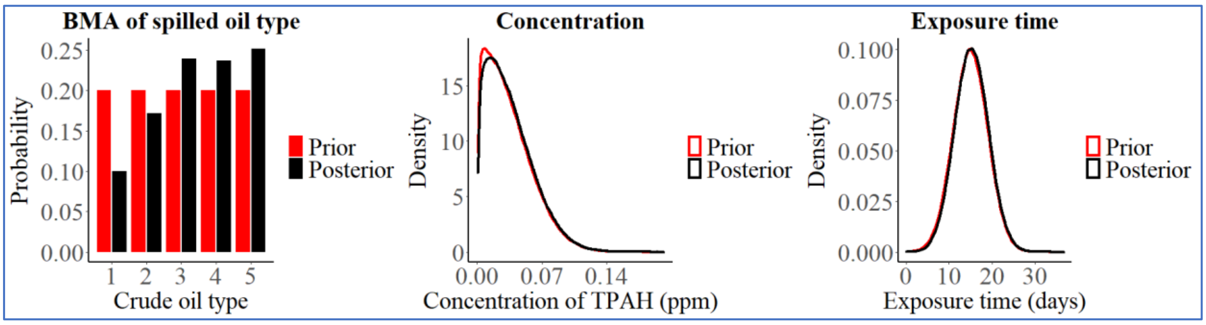


Figure 26, Prior vs. posterior of aspects related to Antonio Gramsci spill of 1987

Exposure time and concentration have not been updated much from prior to posterior. This could be explained by the fact that there is only one data point for updating them. Therefore, the posteriors are mostly affected by the priors. A sensitivity analysis was conducted to determine how much the BMA results are affected by the priors of exposure time and concentration parameters.

There is not much effect on the BMA results when using uniform priors for concentration and exposure time (Figure 27). Again, concentration and exposure time parameters are not significantly affected by updating from prior to posterior. Cook Inlet crude oil has lost some probability and ANSCO has gained a little, but otherwise the BMA results look like the original distribution.

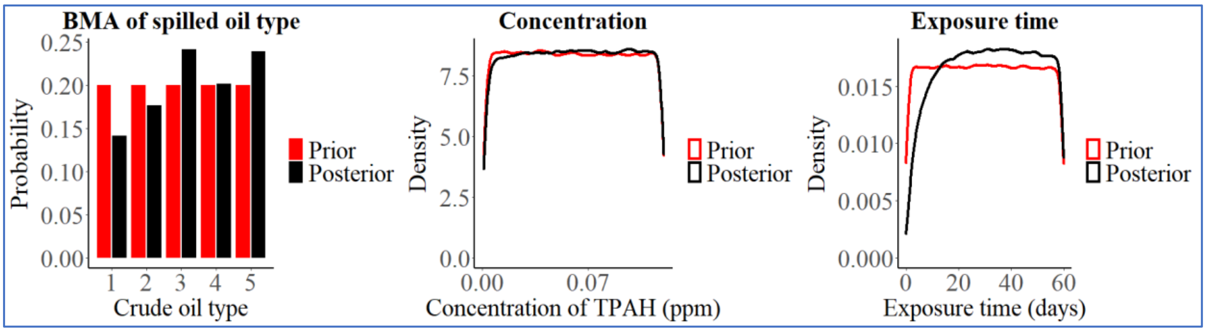


Figure 27, Prior vs. posterior of aspects related to Antonio Gramsci spill of 1987, uniform priors for concentration and exposure time

When using high priors for concentration and exposure time, even more probability is allocated from Cook Inlet crude oil to ANSCO (Figure 28). There is virtually no change in concentration and exposure time from prior to posterior in this case.

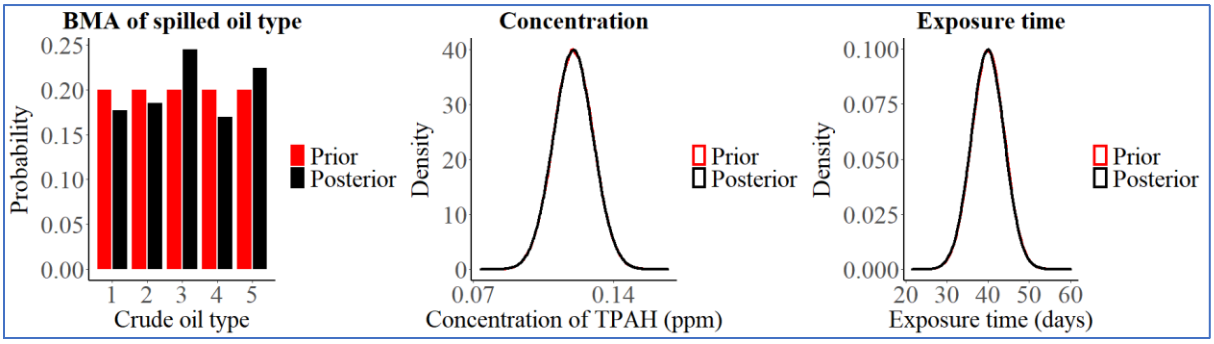


Figure 28, Prior vs. posterior of aspects related to Antonio Gramsci spill of 1987, high priors for concentration and exposure time

Model checking

The model was checked by plotting sorted Bayesian p-values, plotting predicted data from the posterior predictive distribution against the data, and plotting Bayesian p-values against the concentration data in logarithmic scale (Figure 29).

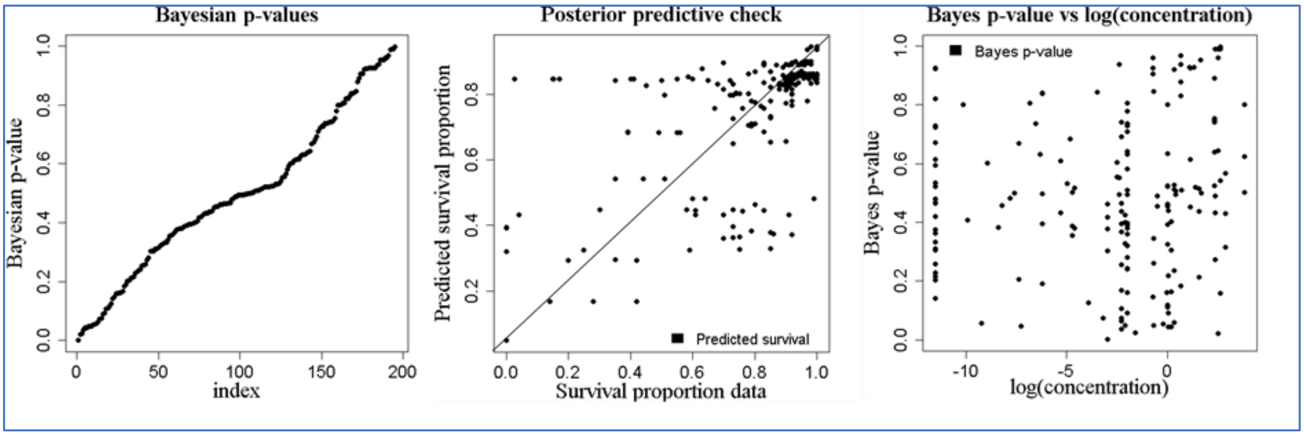


Figure 29, Model checking results

The sorted Bayesian p-values span uniformly from 0 to 1 (Figure 29). This suggests no bias and good fit, at least in terms of marginal variance. The Bayesian p-value calculates whether predictions, given the data, are more extreme than the actual data points. When the sorted p-values span uniformly from 0 to 1, it means predictions done with the model have a 50 % probability of being more extreme than the data points. Therefore, on average the model does not overpredict or underpredict.

Plotting predicted survival proportion data against the actual data, shows visually how well the predictions mimic the data. The predictions seem to mimic the model data quite well, as can be seen from the somewhat uniform distribution of the points on both sides of the diagonal line (Figure 29). The fit of the model can also be checked by plotting Bayes p-values against log(concentration). Since there is no clear pattern evident in the scatterplot (Figure 29), and the points are scattered somewhat evenly across the plot at each log(concentration), the fit seems good.

Finally, correlations between parameters transferred to the prediction model were checked (Figure 30). It seems there is positive correlation between the additional mortality parameters. Light fuel oil seems to be an exception. The standard deviation of total mortality seems to have little negative correlation with some of the additional mortality parameters.

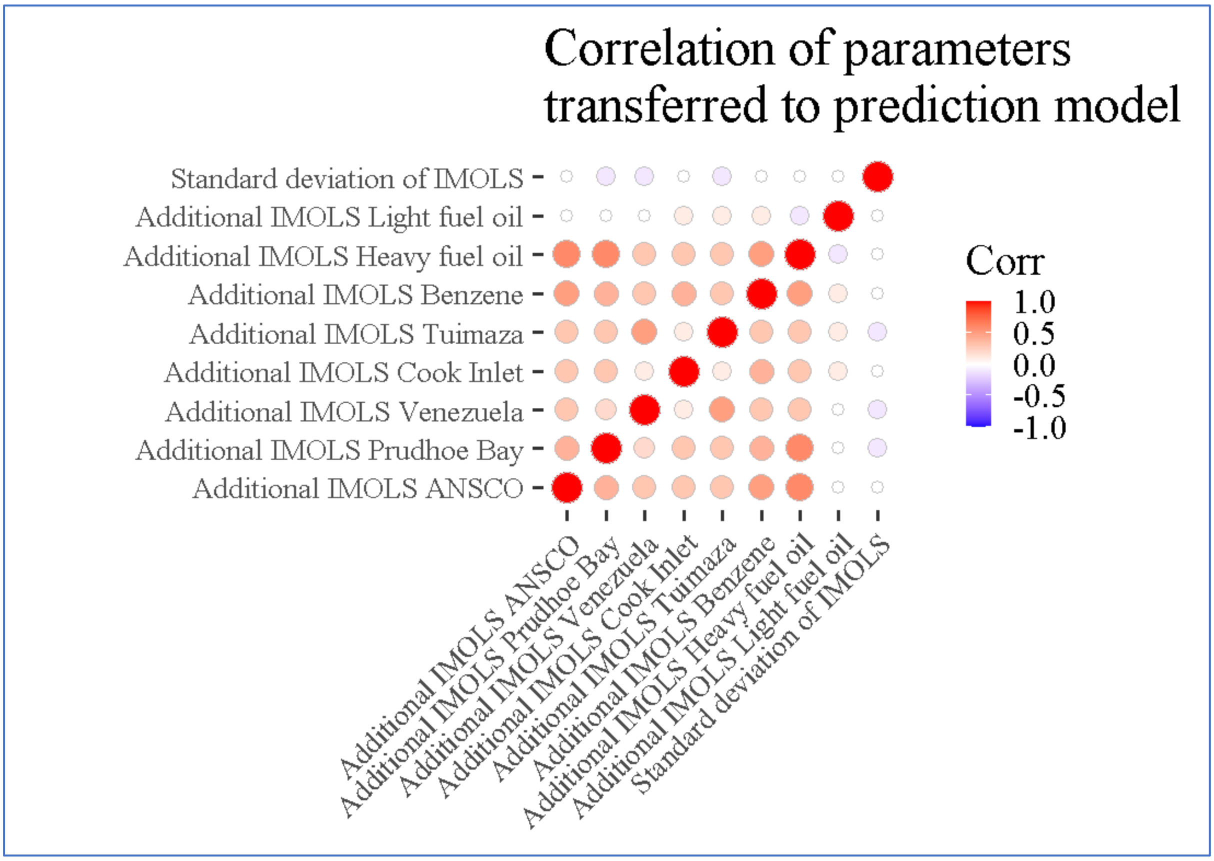


Figure 30, Correlation between transferred parameters

Because there is correlation between the transferred parameters, they will be transferred as a multivariate normal distribution. This way, the correlation can be considered in the predictions.

4.2 Prediction model scenario runs

In addition to the scenarios in Figure 18, the prediction model was run without oil exposure for each of the two initial population states. The scenario results are illustrated with line graphs, in which the black horizontal lines, where y = 0, represent results without oil exposure. Results of the no oil exposure runs were used as reference scenarios to which all oil exposure results were compared to. This section is divided according to the different predicted quantities (Figure 18).

Population abundance results are presented as annual percent changes from the level of no oil exposure scenario. Results regarding value of biomass and catch, are presented as cumulative economic value changes from the level of no oil exposure scenario at the end of prediction period, in millions of Euros. The development of the cumulative economic value changes year by year for each scenario can be seen in Appendix 4.

The results are summarized with expected values and 95 % probability intervals. A 95% probability interval shows the uncertainty regarding the true value of a parameter. Within the interval, lie 95% of the possible true values, leaving out 2.5% from the highest end of values, and 2.5% from the lowest end. A 2.5% quantile tells the lowest value of the 95% probability interval, and a 97.5% quantile tells the highest value of the 95% probability interval. In the results below, the expected values tell the differences between the expected values of the oil spill scenarios and the expected values of the reference scenarios. The quantiles tell the differences between the quantiles of the oil spill scenarios and the quantiles of the reference scenarios.

Oil induced change in population abundance compared to no oil exposure

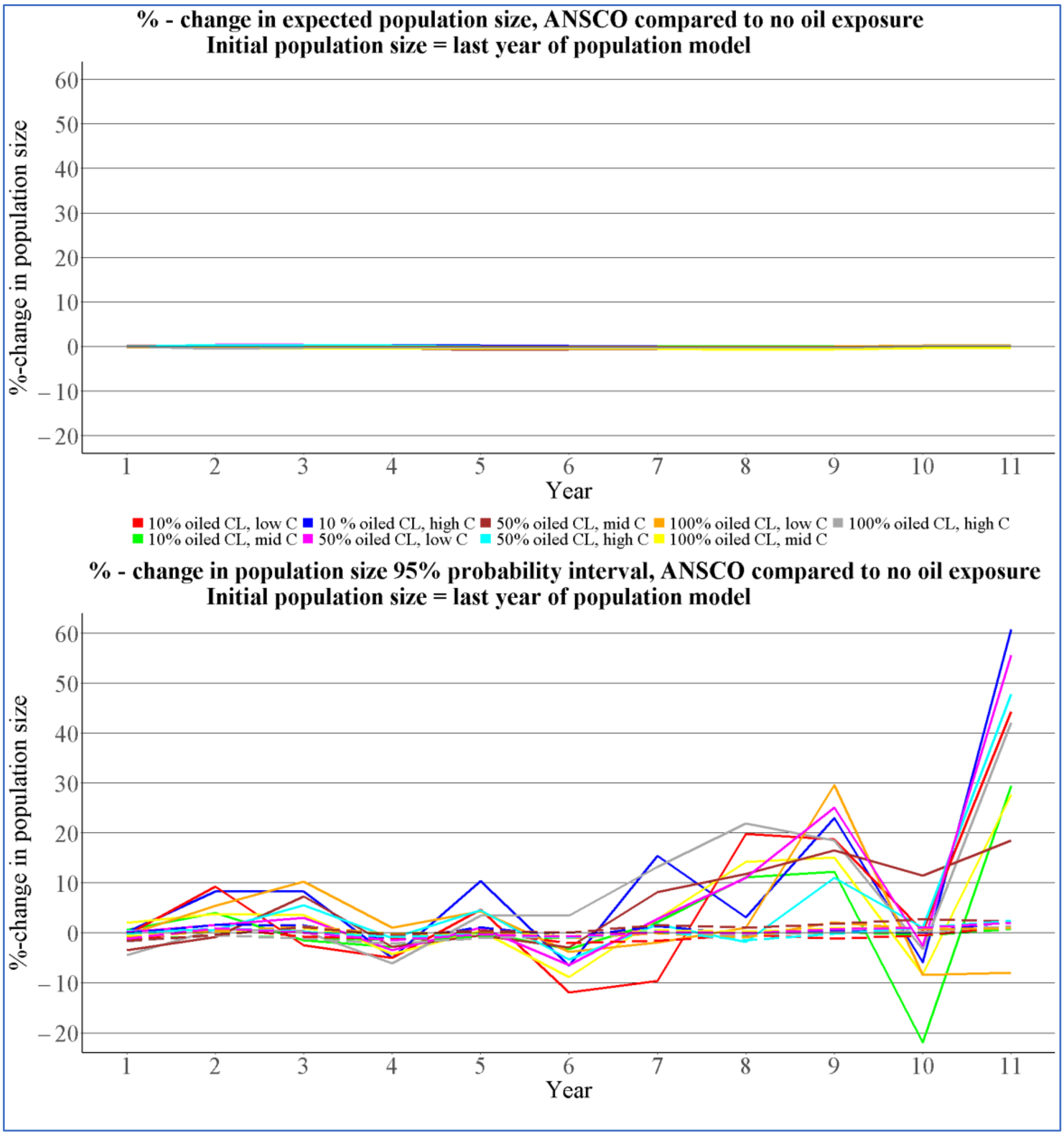


Figure 31, Prediction results: population abundance expected value and 95% probability interval (solid line = 2.5% quantile, dashed line = 97.5% quantile), ANSCO, last year of population model

When initial population abundance was set to the last estimated year of the population model, exposure to ANSCO did not cause significant expected changes from the reference scenario (Figure 31). With exposure to ANSCO, the highest possible true values did not change significantly from the reference scenario. The lowest possible values did change from the reference scenario and, up until year 7, the variation of the changes between the oil spill scenarios was between -10 and 10 percent. After year 7, there was more variation in the changes between the scenarios.

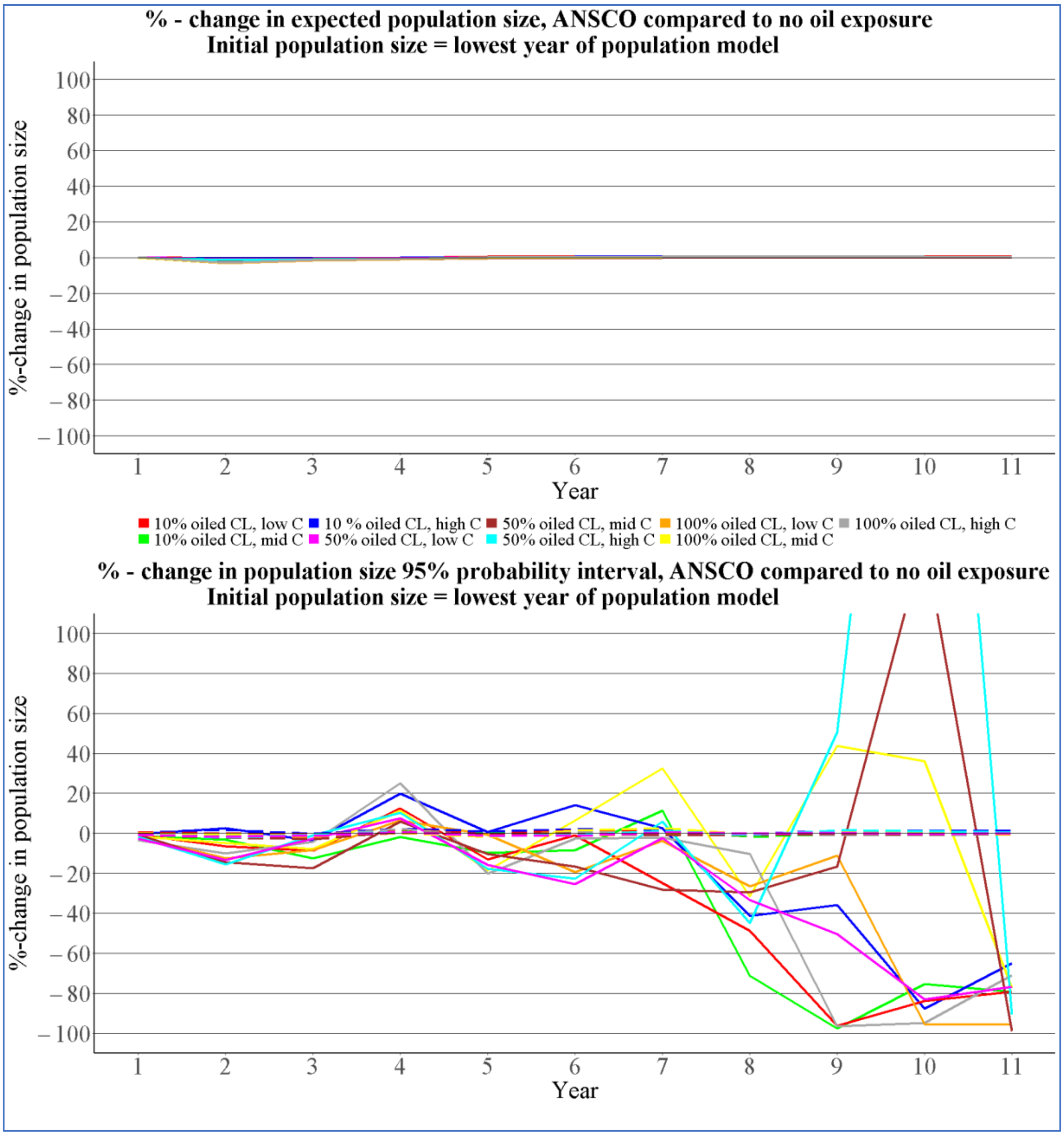


Figure 32, Prediction results: population abundance expected value and 95% probability interval (solid line = 2.5% quantile, dashed line = 97.5% quantile), ANSCO, lowest year of population model

When initial population state was set to the lowest estimated year of the population model, ANSCO exposure caused, in some scenarios, expected population abundance to decrease a few percent from the reference scenario by year 2 (Figure 32). Population abundance quickly recovered to the reference scenario level after year 3. ANSCO's low additional IMOLS per exposure time (Table 4), seems to cause little expected changes in population abundance from the reference scenario, regardless of concentration and proportion of oiled coastline. The highest possible true values did not change significantly from the reference scenario in any of the oil spill scenarios. The changes of the lowest possible true values from the reference scenario, show high variation between oil spill scenarios. Up until year 7, the variation of the changes was between -20 and 20 percent. After year 7, the magnitudes of the changes were larger.

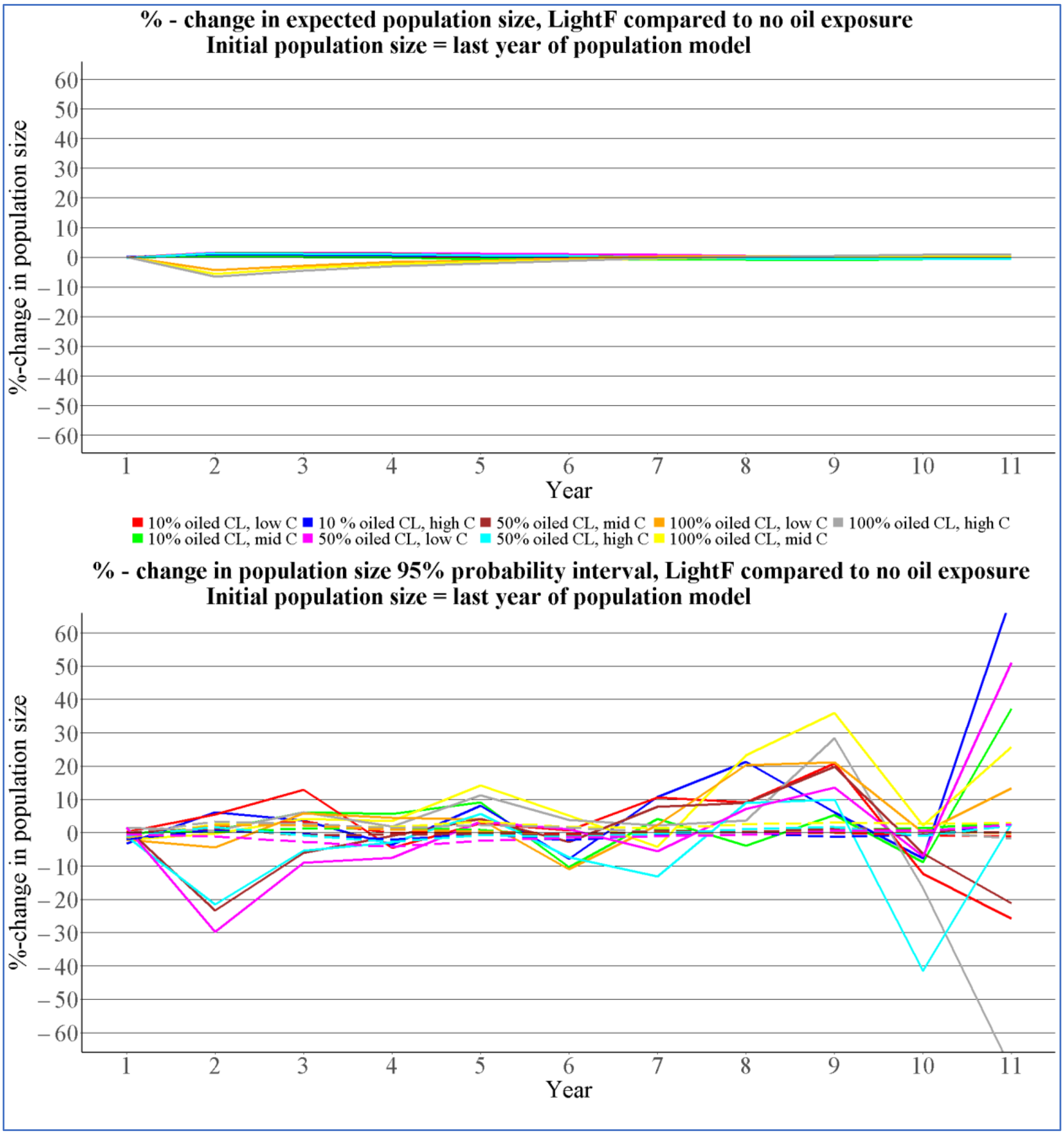


Figure 33, Prediction results: population abundance expected value and 95% probability interval (solid line = 2.5% quantile, dashed line = 97.5% quantile), Light fuel oil, last year of population model

Exposure to light fuel oil caused more significant expected changes in population abundance from the reference scenario, than exposure to ANSCO (Figure 33, Figure 34). Interestingly, when initial population state was set to the last estimated year of the population model (Figure 33), and proportion of oiled coastline was set to 10 or 50 percent, expected change in population abundance from the reference scenario was slightly positive. According to the Ricker model parameterization used in the population model, when initial population abundance, and thus spawned eggs is on a high level, an oil induced decrease in spawned eggs can increase recruitment if the decrease in spawned eggs is not too high. It should be noted here, this thesis does not promote oil spills as a good way to increase herring recruitment. This is merely an effect of the stock-recruitment model assumptions made in the population model. According to the 95% probability interval, the scenarios with 50% oiled coastline had smaller lowest possible true values in year 2 than the reference scenario. After year 2, the variation of the oil spill scenarios' changes in lowest possible true values from the reference scenario, is between -10 and 10 percent. After year 7, the variation between scenarios is larger. The highest possible true values do not differ significantly from the reference scenario.

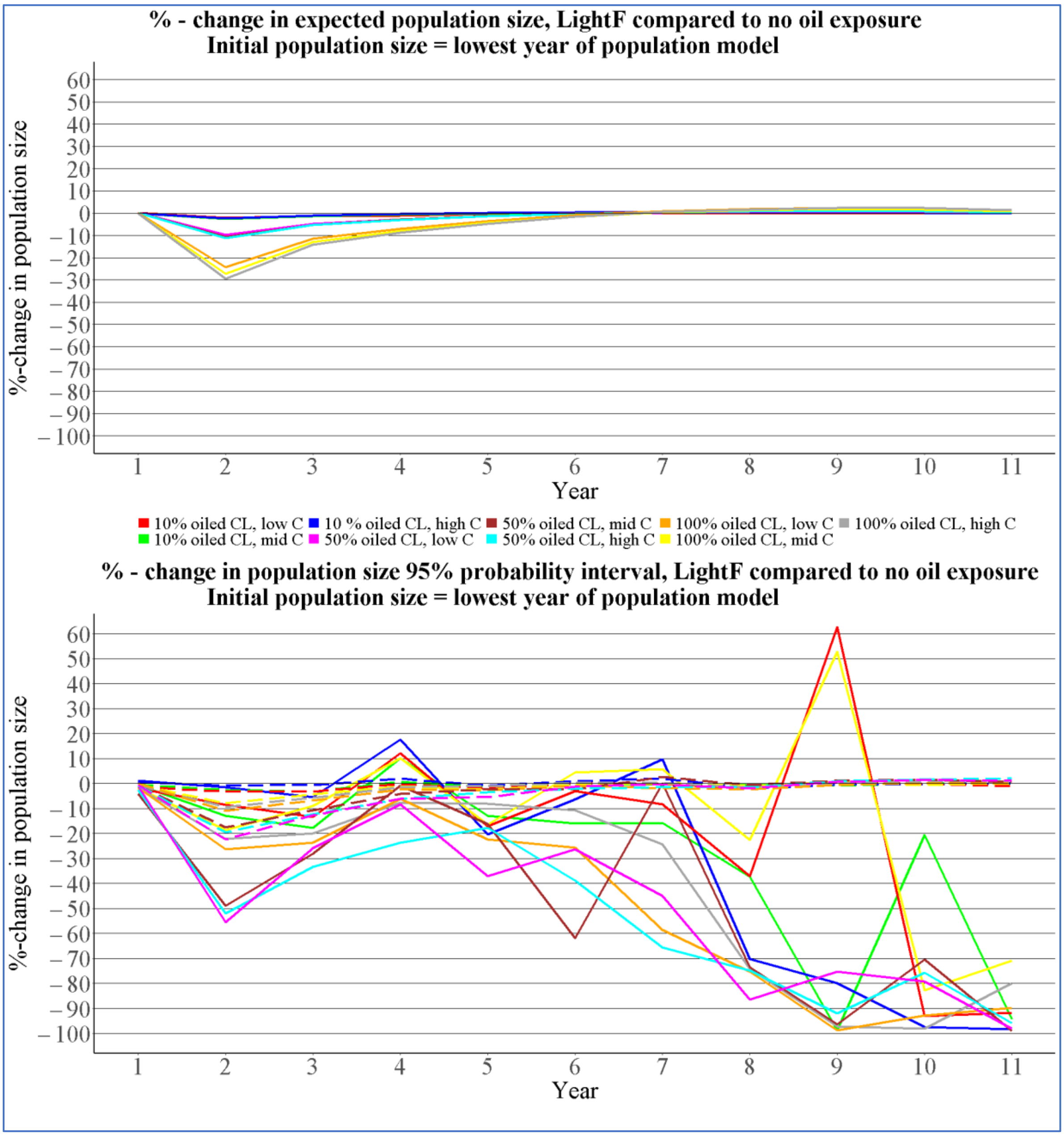


Figure 34, Prediction results: population abundance expected value and 95% probability interval (solid line = 2.5% quantile, dashed line = 97.5% quantile), Light fuel oil, lowest year of population model

According to the Ricker parameterization, when population abundance is on a low level, the number of spawned eggs is low, and density dependent survival of eggs is high. Therefore, a decrease in spawned eggs due to oil exposure, does not yield significant density dependent increase in recruitment. When initial population state was set to the lowest year of the population model, expected population abundance decreased compared to the reference scenario in all oil spill scenarios (Figure 34). According to the results, expected change in population abundance from the reference scenario, has a negative correlation with both concentration and proportion of oiled coastline. According to the 95 % probability interval, the highest possible true values of the oil spill scenarios, were smaller compared to the reference scenario from year 2 to 5. There is much more variation in the changes of the lowest possible true values between oil spill scenarios from the reference scenario, than in the changes highest possible true values. The lowest possible true values are increasingly smaller compared to the reference scenario after year 7, except in 100% oiled coastline scenarios with low and mid concentrations in year 9.

In conclusion, light fuel oil clearly causes population abundance to change more significantly from the reference scenario than ANSCO. With ANSCO exposure, expected changes from the reference scenario were practically nonsignificant. When initial population state was set to the last estimated year of the population model, population abundance increased in some light fuel oil scenarios from the reference scenario level, suggesting favorable effect on recruitment due to Ricker model parameterization. When population state was set to the lowest estimated year of the population model, the expected changes from the reference scenario in the light fuel oil scenarios were most significant. In scenarios with 100% oiled coastline, the expected change was around -30 percent. The 95 percent probability intervals suggest little difference between highest possible true values of the scenarios and highest possible true values of the reference scenario. The lowest possible true values of the scenarios differed significantly from the reference scenario. The variation of the lowest possible true value changes between the oil spill scenarios, increased significantly from year 6 or 7 onwards, possibly indicating increasing uncertainty in later prediction years.

Impact of ANSCO exposure on the economic value changes of total biomass compared to no oil exposure

Exposure to ANSCO, when initial population state was set to the last estimated year of population model, caused expected cumulative economic value of total biomass at the end of the prediction period to increase from the reference level in most scenarios (Figure 35). This is most likely due to Ricker model parameterization. Cumulative 95 percent probability intervals show the uncertainty regarding the true values of cumulative economic value change of total biomass from the reference scenario. There was much variation in the changes in the lowest and highest possible true values across the oil spill scenarios.

When initial population state was set to the lowest estimated year of the population model, all scenarios yielded negative expected cumulative value changes from the reference scenario (Figure 35). When number of spawned eggs is proportionally low, a decrease in eggs does not yield density dependent advantages in recruitment, according to the Ricker model parameterization. Interestingly, the scenario with 50 % oiled coastline and mid concentration of TPAH in water, yielded larger expected cumulative value decrease from reference scenario level, than scenarios with 100 % oiled coastline.

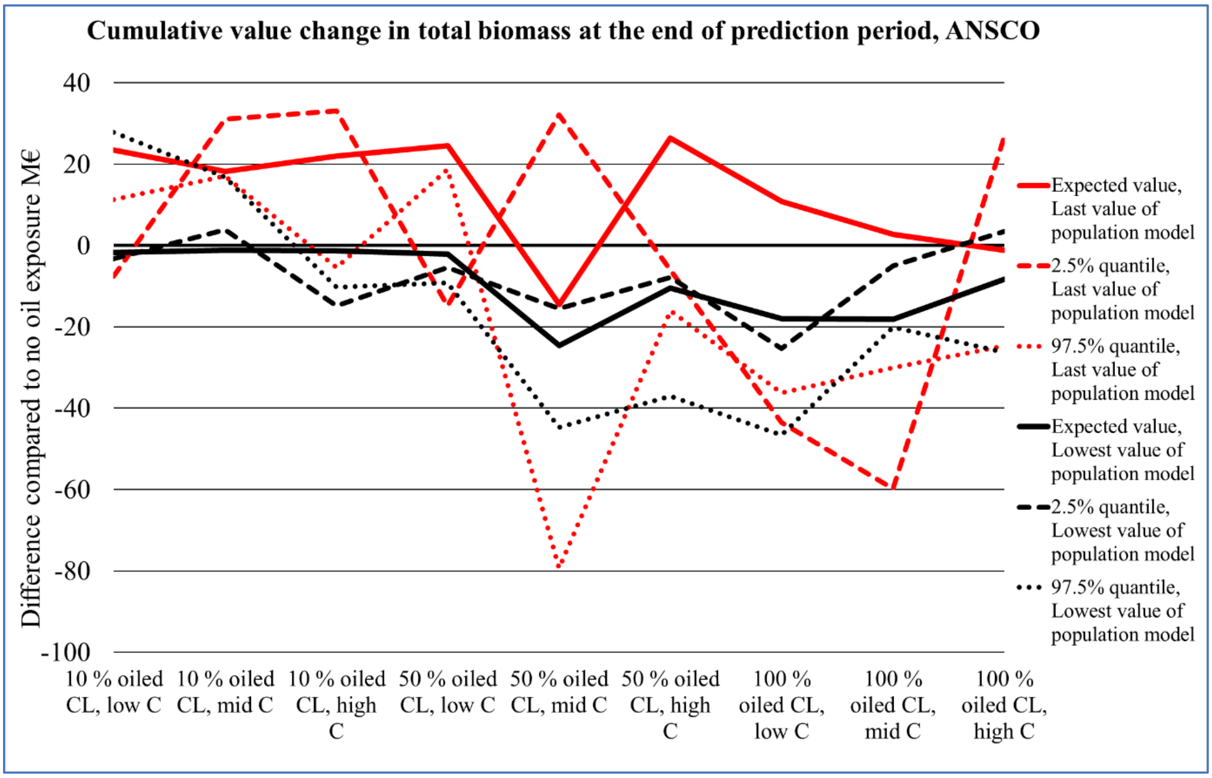


Figure 35, Prediction model results: economic value change in total biomass from the level of no oil exposure, ANSCO

When initial population state was set to the lowest estimated year of the population model, the changes of the highest possible true values from the reference scenario level became increasingly negative, as oiled coastline rose from 10 to 50 %. The changes of the lowest possible true values from the reference scenario showed a similar trend, but not as steep.

Impact of ANSCO exposure on the economic value change of total catch compared to no oil exposure

According to the oil spill scenario results, changes in cumulative total catch values from the reference scenario, are smaller in magnitude compared to changes in cumulative total biomass value. This is not surprising, since fishing mortality is only a proportion of total biomass. When initial population state was set to the last estimated year of the population model, the expected changes in cumulative total catch value from the reference scenario, were in all oil spill scenarios positive or close to zero (Figure 36). This is most likely due to Ricker model parameterization. The variation of the changes in expected values from the reference scenario across oil spill scenarios, was between 0 and 5 M€. The lowest possible true values of the oil spill scenarios did not differ significantly from the reference scenario. The highest possible true values were mostly higher than in the reference scenario.

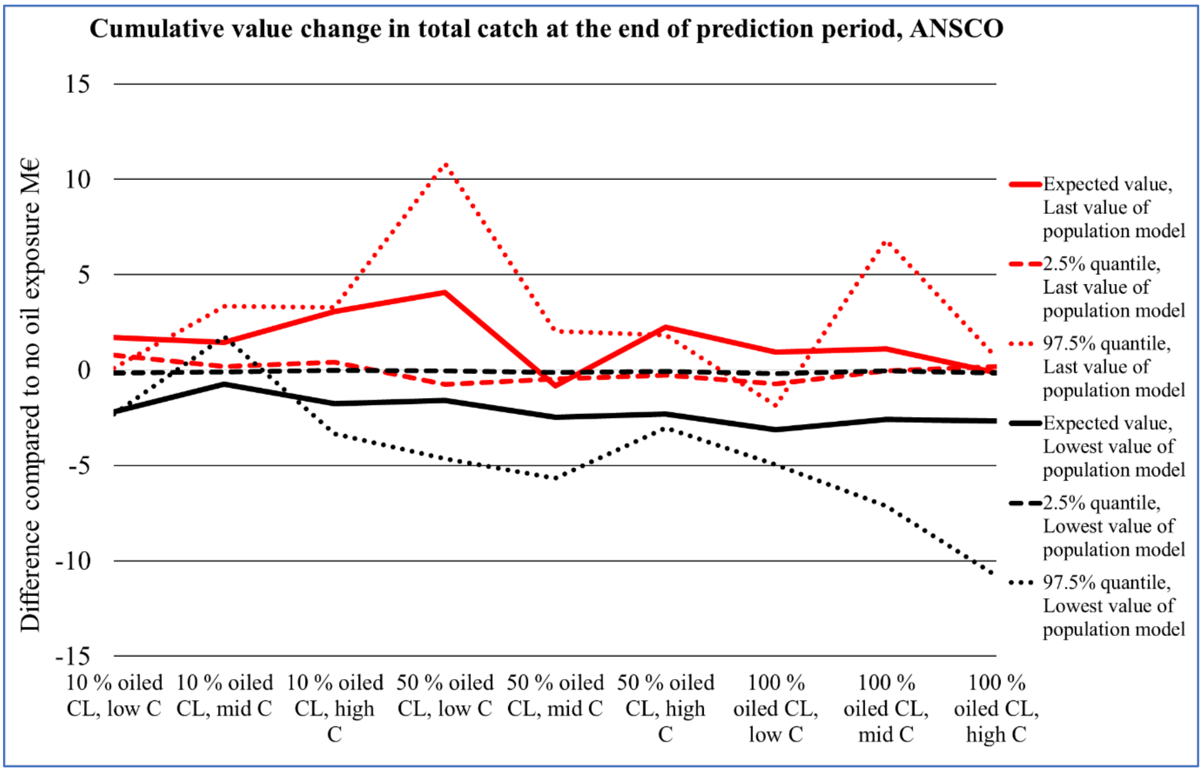


Figure 36, Prediction model results: economic value change in total catch compared to no oil exposure, ANSCO

When initial population state was set to lowest estimated year of the population model, the expected changes in cumulative values of total catch from the reference scenario level, were negative in all scenarios. The variation of the expected changes across the oil spill scenarios, was steady between -3 and 0 M€. The lowest possible true values did not differ from the reference scenario. The changes of the highest possible true values from the reference scenario, were increasingly negative as oiled coastline rose from 10 to 100 %.

Impact of light fuel oil exposure on the economic value change of total biomass compared to no oil exposure

According to the results, changes in value of total biomass from the reference scenario are greater in magnitude with light fuel exposure than with ANSCO exposure (Figure 37).

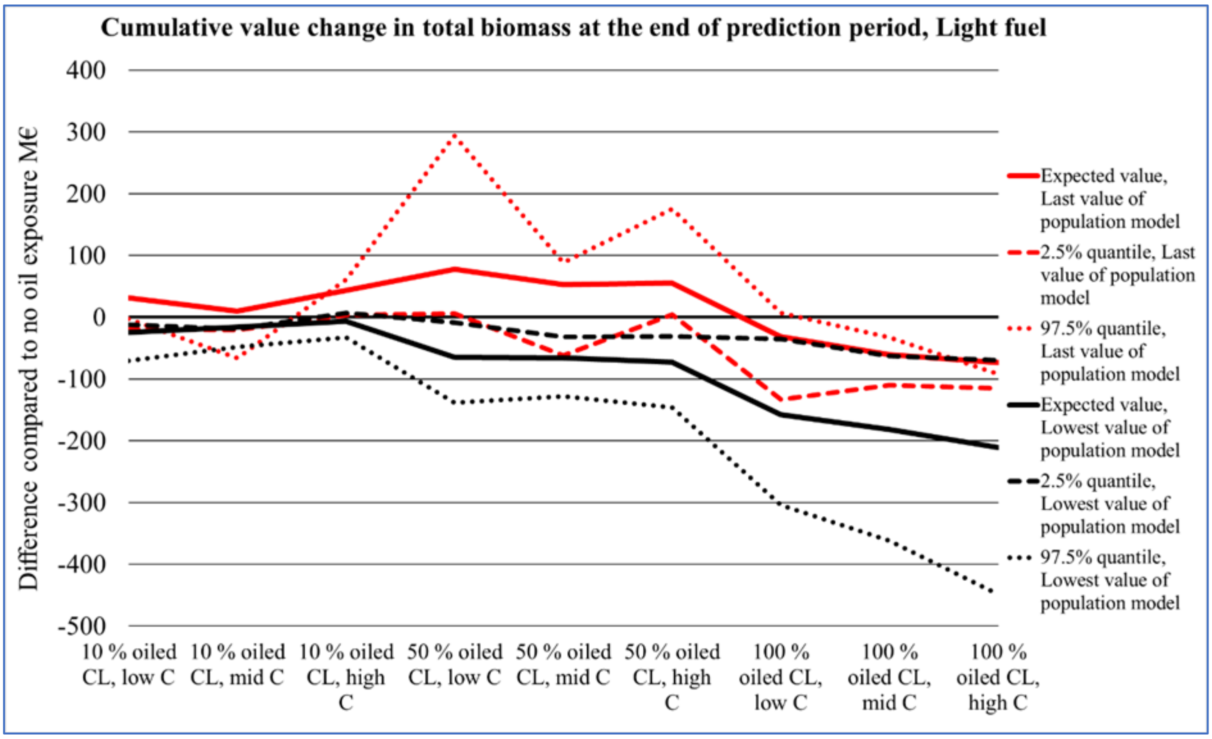


Figure 37, Prediction model results: economic value change in total biomass compared to no oil exposure, Light fuel oil

When initial population state was set to the last estimated year of the population model, scenarios with 10 and 50 % oiled coastlines resulted in expected cumulative value increases compared to the reference scenario, most likely due to Ricker model parameterization. Scenarios with 100 % oiled coastline resulted in value decreases (Figure 37). 50 % oiled coastline scenarios yielded most value increase. In 100 % oiled coastline scenarios, value decrease had positive correlation with concentration. The variation of the expected changes in cumulative total biomass value from the reference scenario, was between -100 and 100 M€. The lowest possible true values did not differ significantly compared to the reference scenario in 10 and 50 % oiled coastline scenarios, except for the scenario with 50 % oiled coastline and mid concentration. The changes in the highest possible true values compared to the reference scenario, were more significant. The changes were mostly positive, most likely due to Ricker model parameterization.

With the lowest estimated year of the population model as the initial population state, the expected changes in cumulative total biomass value from the reference scenario were negative in all oil spill scenarios (Figure 37). The trend of the expected changes was increasingly negative, as oiled coastline proportion rose from 10 to 100 %. The variation of expected changes across scenarios, was between -200 and 0 M€. The changes of the lowest possible true values of the oil spill scenarios from the reference scenario level, showed an increasingly negative trend as oiled coastline rose from 50 % to 100 %. The highest possible true values differed more from the reference scenario than the lowest possible values. The changes in the highest possible true values from the reference scenario level, had an increasingly negative trend. The variation of the changes across the oil spill scenarios was between -450 and -30 M€.

Impact of light fuel oil exposure on the economic value change of total catch compared to no oil exposure

Like with ANSCO exposure scenarios, the changes in cumulative economic values of total catch from the reference scenario level are smaller in magnitude than changes in the expected cumulative total biomass values (Figure 38). When initial population state was set to the last estimated year of the population model, the expected changes of the cumulative values compared to the reference scenario were positive, except for scenarios with 100 % oiled coastline. The increases in value, compared to the reference scenario, are most likely due to Ricker model parameterization. The variation of the expected changes in value across the oil spill scenarios is between -4 and 8 M€. According to the 95 % probability interval, the lowest possible true values of the oil spill scenarios did not differ from the corresponding values of the reference scenario. The changes in the highest possible true values of the scenarios, from the reference scenario level, were all positive. The highest positive changes were yielded in scenarios with 50 % oiled coastline.

When the initial population state was set to lowest estimated year of the population model, all expected changes in cumulative total catch value from the reference scenario level were negative (Figure 38). The changes show an increasingly negative trend across scenarios, as proportion of oiled coastline and concentration increase. The variation of the changes across scenarios is between -20 and 0 M€. The lowest possible true values of total catch value do not differ from the reference scenario. The variation of the changes in highest possible true values across oil spill scenarios is between -50 to -3 M€. The changes in highest possible true values from the reference scenario level show an increasingly negative trend as proportion of oiled coastline and concentration increase.

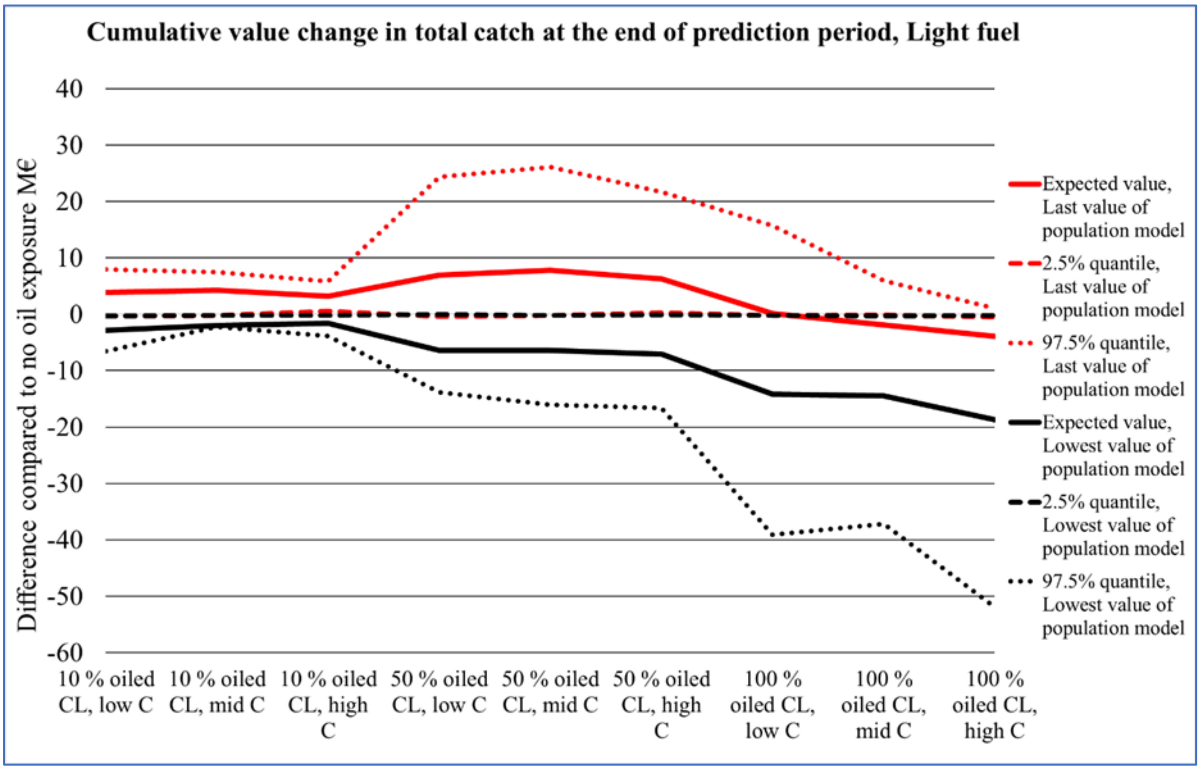


Figure 38, Prediction model results: economic value change in total catch compared to no oil exposure, Light fuel oil

As a conclusion it can be stated that as the oil type and initial population state are fixed, the patterns of the expected changes in cumulative total biomass values from the reference scenario, resemble the patterns of the expected changes in cumulative catch values from the reference scenario. This indicates that there are no changes in fishing mortality in the population model due to oil exposure and furthermore, as biomass decreases so do the catches in same proportions. According to the results, the highest possible true values of the cumulative catch values in the scenarios do not differ from the reference scenario. In general, the highest possible true values of total biomass of the oil spill scenarios differ less from the reference scenario, than do the lowest possible values.

Impacts of the oil exposures on economic values calculated per recruit of the no oil exposure scenarios: total biomass

To make the results transferable to other environments, the expected changes in values from the reference scenarios are presented per recruit, by dividing them with number of recruits in the no oil exposure reference scenarios (Figure 39, Figure 40).

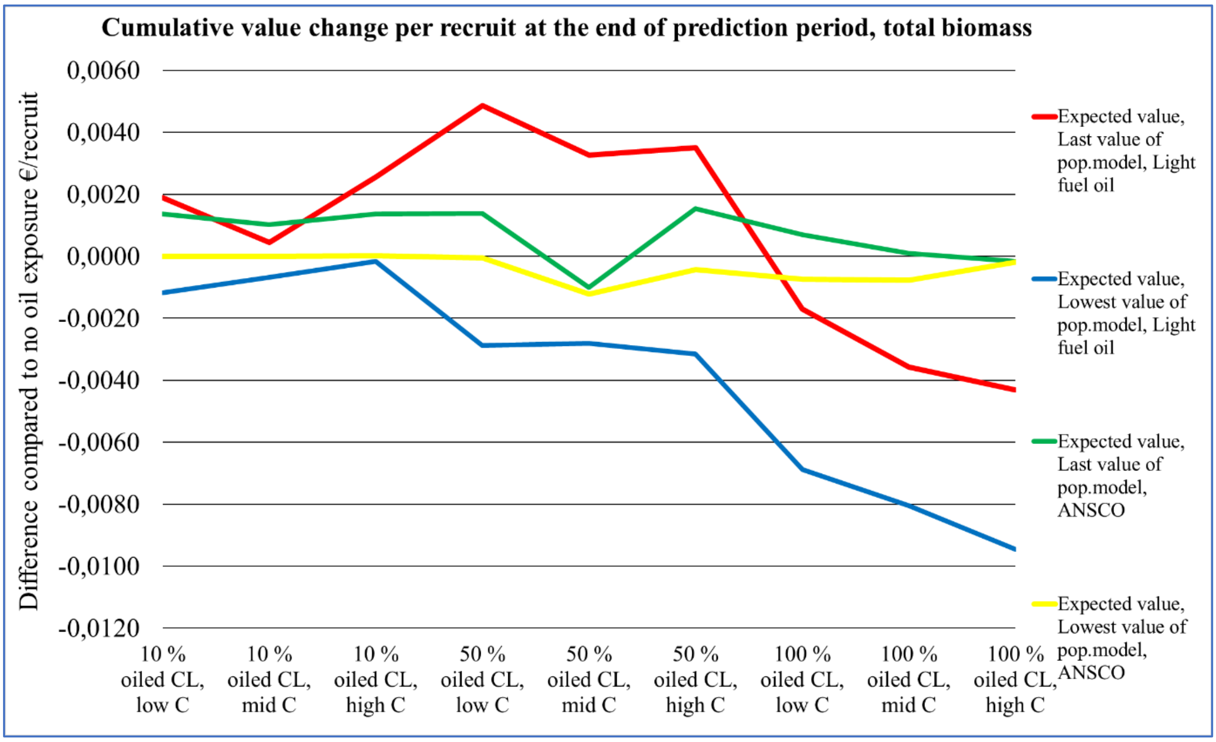


Figure 39, Prediction results: Expected differences in value of total biomass calculated per recruit

When initial population state was set to the last estimated year of population model, exposure to ANSCO yielded expected changes in the cumulative value of total biomass from the reference scenario between -0.001 and 0.002 € per recruit. When initial population state was set to the lowest estimated year of the population model, the results with ANSCO exposure were between -0.0012 and 0 € per recruit. With each initial population state, and with ANSCO exposure, the most negative changes in value of total biomass from the reference scenarios, are achieved in scenarios with 50 percent oiled coastline and mid concentration. This could have something to do with the characteristic of the Ricker model parameterization.

Exposure to light fuel oil, when initial population state was set to the last estimated year of the population model, yielded expected changes in cumulative economic value of total biomass from the reference scenario between -0.004 and 0.005 Euros per recruit, depending on the scenario. The scenarios, resulting in value increases from the reference scenario, do so most likely due to the Ricker model parameterization. It appears 50 percent oiled coastline yields most value increase from the reference scenario. When initial population state was set to the lowest estimated year of the population model, all results were value decreases from the reference scenario. For scenarios with 50 and 100 percent oiled coastlines, positive correlation between value decrease, concentration, and oiled coastline was evident. For scenarios with 10 percent oiled coastline, concentration was negatively correlated with value decrease. This effect is most likely due to the Ricker model parameterization. Expected changes in cumulative economic total biomass values from the reference scenario seem to lie between -0.010 and 0 Euros per recruit.

Impacts of the oil exposures on economic values calculated per recruit of the no oil exposure scenarios: total catch

According to the per recruit results, the expected changes in the cumulative values of catches from the reference scenario, are approximately ten times smaller than the corresponding results in expected value of total biomass (Figure, 40). This indicates fishing mortality is approximately 10 % of the total biomass.

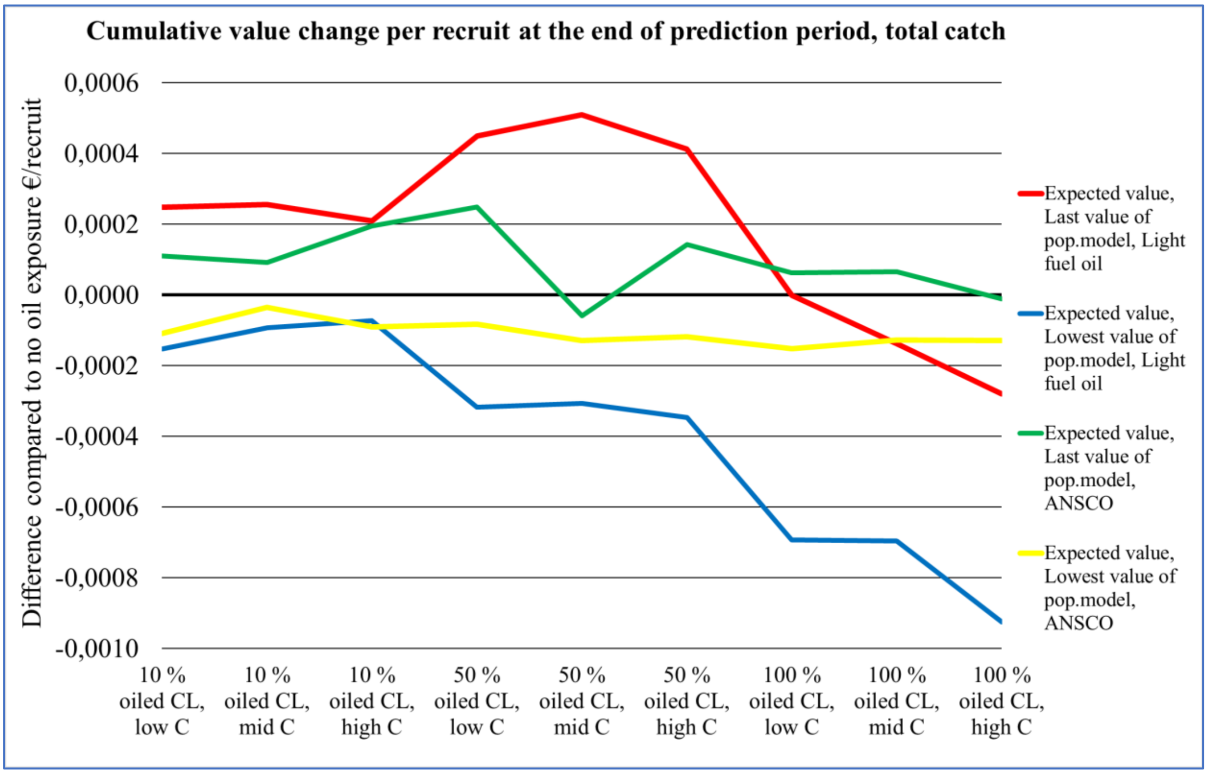


Figure 40, Prediction results: Expected differences in value of total catch calculated per recruit

When initial population state was set to the last estimated year of the population model, and with ANSCO exposure, expected changes in the cumulative values of catch from the reference scenario, are between -0.0001 and 0.00025 € per recruit. When initial population state was set to lowest year of the population model, the corresponding values are between -0.0002 and 0 € per recruit.

When initial population state was set to the last estimated year of the population model, and with light fuel exposure, the expected changes in cumulative value of catches from the reference scenario, were between -0.0003 and 0.0005 € per recruit. The highest positive differences in value are yielded with 50% oiled coastline scenarios. When initial population state was set to the lowest estimated year of the population model, the expected changes in cumulative values of catch from the reference scenario were all negative between -0.001 and -0.0001 € per recruit.

5 Discussion and conclusions

Assessing oil spill impact on Baltic Sea herring: 1. Impact on population

The main purpose of this study was to develop a hierarchical bioeconomic Bayesian prediction model for predicting oil spill impacts on Baltic Sea herring population, through oil induced additional egg mortality. Furthermore, the predictions of the impacts on the population, were supposed to be used to determine financial impacts to fishermen. These aims were achieved very well in the prediction model that was developed in this thesis. In this chapter the main achievements of the results and future development areas for the model are discussed. The thesis and the discussion are then concluded in the final conclusions.

The predicted quantities of the prediction model scenarios do not directly show mortality of eggs. The oil type specific additional instantaneous mortalities on log scale (IMOLS), estimated with the modified meta-analysis model, were transformed to mortality proportions, with which the number of spawned eggs was directly decreased within the prediction model design. The prediction model scenario results showed how this decrease in spawned eggs affected population dynamics parameters, and consequently financial impacts to fishermen. In this section the assessed impact on population abundance is discussed. The financial impacts are discussed in the next section.

The results of this study indicated similar relationships between oil induced additional mortality of herring eggs and oil spill characteristics, as found in the literature review. According to the literature review, oil type affects the magnitude of additional mortality of oil. Generally, lighter oils are found to be more lethal than heavier oils. In the modified meta-analysis model, individual oil's weight, expressed with an API covariate, was assumed to be the main oil type related explanatory factor of oil type specific additional IMOLS of herring eggs. To consider the unique compositions and characteristics of different oils, each oil in the data set was analyzed separately in this thesis, in contrast to the original meta-analysis in Raubenheimer et al. (unpublished).

In the modified meta-analysis model run results in section 4.1, lighter oils were found more lethal in general with some exceptions. For example, according to the API covariate value found in literature, Prudhoe Bay crude oil is heavier than ANSCO, but the results indicated it to be more lethal. The reason for this, is most likely in part the fact that there are numerous other factors to consider as explanatory factors of oil lethality. Therefore, the model developed in this thesis should be expanded to include the consideration of these factors, such as precise PAH composition of an oil and its weathering. Weathering rate of an oil is in turn dependent on external conditions, which should be considered in the model structure, and linked with causal relationships to oil induced additional IMOLS. There is as well, uncertainty related to the API covariate values that were found in literature. The type of oil, and its origin, might not be correctly disclosed in the studies of the data set. In addition, the reported API figures for different oil types vary in literature, and even the definition of API can vary across different studies. Determining an accurate description for oil's lethality, for example by using Bayesian meta-analysis techniques, is an important subject for future research.

In addition to oil type, the literature review found other important oil spill characteristics for assessing oil spill impact on herring egg mortality, such as concentration of TPAH in water, exposure time of eggs to PAHs, and proportion of oiled coastline in herring spawning grounds. The effects of these characteristics on Baltic Sea herring population, including oil type, were demonstrated with the hypothetical oil spill scenarios in the prediction model runs, except for exposure time, which was kept on the same level in all scenarios because of time constraints.

In the literature review, initial concentration of TPAH in water was stated to be positively correlated with oil induced additional mortality of herring eggs. The modified meta-analysis model was designed to increase additional IMOLS per exposure time of herring eggs as a function of TPAH concentration on log scale. The results from the different prediction scenarios showed how changing initial concentration of TPAH in water, and consequentially changing number of spawned eggs after oil exposure, affected population dynamics parameter values. The effect of concentration was best seen in scenarios with light fuel oil, in which the results of different scenarios had clearer differences. In these scenarios, higher concentration could be seen to produce larger changes in population abundance from the reference scenario. The effect of the proportion of oiled coastline was, similarly to concentration, best evident in light fuel oil scenarios, where larger proportions of oiled coastline resulted in higher changes in population abundance from the reference scenario. The magnitudes of the changes from the reference scenarios were larger in light fuel oil scenarios than in ANSCO scenarios.

A very interesting finding was made from the prediction scenario results. It appears the assumption of density dependent survival of eggs of the Ricker model used in the population dynamics model, determines partly how additional egg mortality affects predicted population dynamics parameters in the end (Figure 41). In the population model, two possible density dependent stock-recruitment relationship models were used to describe the true relationship. They were weighted equally likely a priori and their posterior probabilities were 97 % for Ricker model, and 3 % for Beverton-Holt model.

Because of Ricker model's high posterior probability, density dependence was analyzed only in relation to the Ricker model.

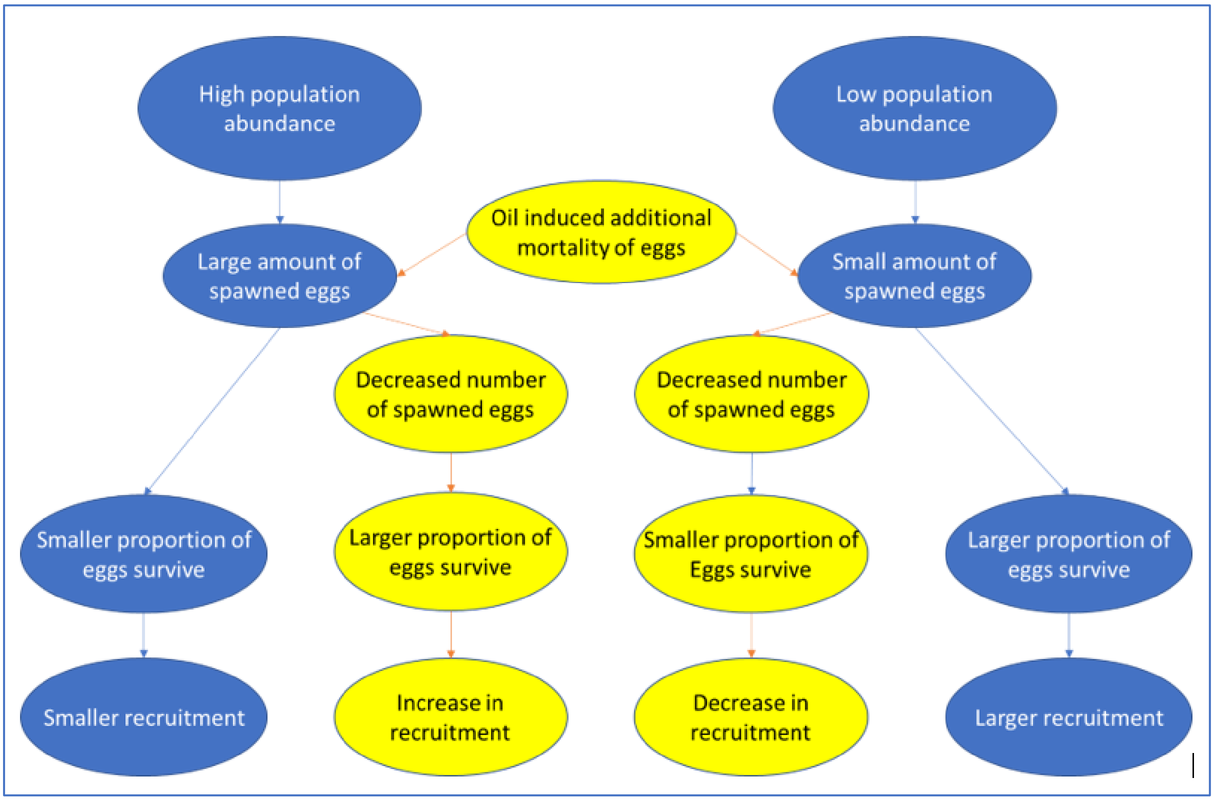


Figure 41, Effect of the Ricker model on predicted quantities

In some of the scenarios, when initial population state in the prediction scenarios was set to the last estimated year of the population model, corresponding a high population abundance, an oil induced decrease in spawned eggs caused an increase in population abundance from the reference scenario level. On the other hand, in most of the scenarios, when population state was set to the lowest estimated year of the population model, corresponding a low population abundance, a decrease in spawned eggs lowered population abundance. This might be at least in part due to the density dependent mechanism of the Ricker model parameterization.

In the population model by Mäntyniemi et al. (2013a), the parameterization of the Ricker model, and calculation of recruits, are derived from survived eggs. Proportion of survived eggs is higher when number of spawned eggs is lower and vice versa. Therefore, when number of spawned eggs is high, due to high population abundance, the Ricker model increases exponentially the proportion eggs that survive to recruits, after oil exposure has first decreased the number of spawned eggs. The increase in recruitment is higher than the decrease in spawned eggs due to oil. On the other hand, if number of spawned eggs is already low, due to low population abundance, an oil induced decrease in number of spawned eggs does not raise the density dependent survival proportion of eggs to recruits after oil exposure, more than what the decrease in number of spawned eggs is. Therefore, recruitment is decreased.

The Ricker model effects are present in the predictions because, in Mäntyniemi et al.'s (2013a) analysis, the model's posterior probability of being the true model for describing stock-recruitment relationship is high. However, the model is only compared to Beverton-Holt model. Therefore, Ricker model assumption in the population model, should be tested against other models from assessments of populations like the one being analyzed. Mäntyniemi et al. (2013a) recognize the need for testing their stock-recruitment relationship assumptions in their discussion. It is important in any fish stock assessment, and in oil impact assessment, to estimate, as well as possible, the prevalent true stock-recruitment relationship.

The effects of the Ricker model had limits in the prediction scenarios. For example, in the scenarios with light fuel oil, initial population state set to last estimated year of the population model, and with 10 and 50 percent oiled coastlines, oil induced additional mortality of eggs caused the population abundance to increase from the level of the reference scenario. However, when proportion of oiled coastline was increased to 100 percent, the decrease in the number of spawned eggs due to oil exposure must have been so significant that it suppressed the Ricker model effects.

The effects of the Ricker model were best seen in light fuel oil scenarios, in which the magnitude of the changes from the reference scenario were much greater. ANSCO caused much less change in all oil spill scenarios. The additional IMOLS caused by ANSCO, as determined by the modified meta-analysis model, is so low it does not seem to have a significant effect on the simulated fish population. That is, at least with the assumptions and data used in the developed model. Using one more crude oil from the dataset, who's additional IMOLS is higher, for example Venezuela crude oil, could have yielded better comparisons for discussion.

It should be noted here that the purpose of this thesis is not to promote, or suggest, that oil spills are a good thing for fish populations. The observed Ricker model effect, in the context of the developed model, does not consider the source of the decrease in spawned eggs. The decrease could have happened because of predation or environmental conditions, and the results would have been similar. The harmfulness of oil to the environment, and to other life stages of herring, are not considered in the developed model structure. These are, however, very important subjects for future research.

Assessing oil spill impact on Baltic Sea herring: 2. Impact on financial values

The prediction scenarios were used to estimate financial impacts to fishermen, after the hypothetical spills had happened. Calculations of the impacts were done by multiplying biomass and catch observable parameter estimates, with a price per kg multiplier. The multiplier was constant for all sizes of herring for simplicity. This might be an oversimplification of the true effects on economic values. For example, the model developed in this study considers the price of herring to be unaffected by changes in demand and supply. The model should be developed further to consider effects of, for example, supply and demand and herring size classes on prices. Furthermore, the economic impacts were estimated only from the oil induced mortality of herring eggs. To estimate total economic impacts, oil effects to other life stages of herring, and to herring environments, should be considered.

The model does not consider changes in fishing mortality after a hypothetical spill has happened. Most likely there would be restrictions, or even halts, on fishing after an oil spill, potentially for a long time like in the case of the Gulf of Mexico spill (Berenshtein et al., 2019). Therefore, the model should be run in the future, by assuming, for example, a three-year halt on fishing all together by assigning fishing mortality to zero. This would have an increasing effect on the negative value changes of catches from the reference scenario. There would of course be decreases in variable costs due to vessels standing in ports, which should be considered in the model as well.

According to the results, expected changes in cumulative values of total biomass are always significantly larger than expected cumulative changes in values of catches (Figure 42). This makes sense since fishing mortality is always only a proportion from total biomass and, according to the results, the proportion of fishing mortality from total biomass seems to be around 0.1. Like the population abundance predictions, the predictions of changes in cumulative values showed results of bigger magnitude in scenarios with light fuel oil than with ANSCO. This makes sense in the light of the additional IMOLS results of the modified meta-analysis model. The effect of concentration and proportion of oiled coastline were most evident in light fuel scenarios. ANSCO caused significantly smaller differences compared to no oil exposure than light fuel oil. Light fuel is significantly lighter than ANSCO, at least according to the API covariate values found in literature, and thus more lethal according to the modified meta-analysis model.

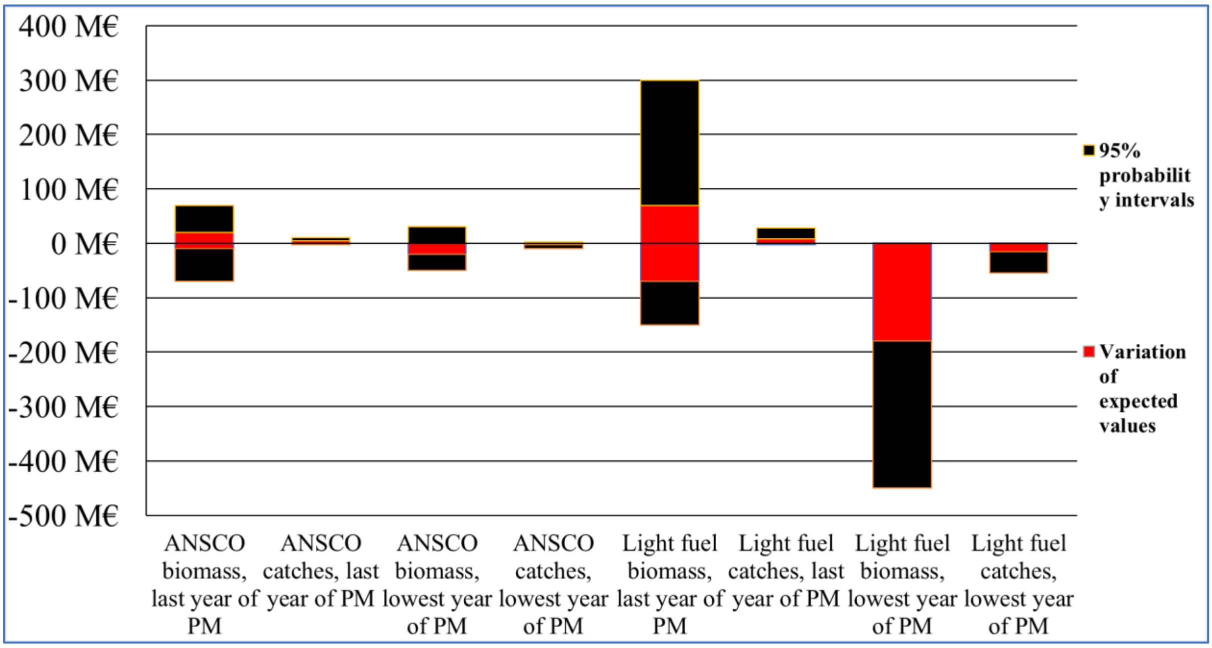


Figure 42, Prediction results: Cumulative difference in value, biomass vs. catches and ANSCO vs. light fuel oil (Black areas behind red areas represent 95 % probability intervals, red areas in front represent the variability of expected values)

Since the predictions of changes in cumulative values are derived straight from population dynamics parameter values with a multiplier parameter, the Ricker model effects are present in the changes in cumulative values as well. When initial population abundance was set to the last estimated year of the population model, most of the predicted changes in cumulative values are positive for both oil types, and for both catches and total biomass. Again, it should be noted, this thesis is not suggesting oil spills are good for fish populations, but rather that these results illustrate the effects of density dependent survival of eggs according to the Ricker model parameterization. This underlines the importance of understanding the true stock-recruitment relationship of a fish population in both stock assessment and oil impact assessment. The model developed in this thesis only considers oil effects on herring egg mortality and ignores other harmful and lethal direct or indirect effects of oil on biota. When population state is set to the lowest estimated year of the population model, the predicted changes in cumulative values were mostly negative for both oils, and for both catches and total biomass.

The greatest negative changes in cumulative values of catches and total biomass from the reference scenario, were caused in scenarios where initial population state was set to the lowest value of the population model, and where oil type was light fuel oil. For total biomass, the largest possible negative change in cumulative value was about -450 million Euros. For catches the same was about -55 million Euros. The changes in cumulative values of catches, are dependent on annual predicted fishing mortalities in the prediction years and, as noted before, after an oil spill there would most likely be a halt on fishing for some time. This would decrease herring fishermen’s revenue to zero, but also decrease variable costs for the duration of the halt. The changes in cumulative value of total biomass from the reference scenario, can be thought to represent the cumulative change in total present and future fishing potential from the reference scenario level at the end of the prediction period.

To make the cumulative value change results transferrable to other herring areas, they were calculated per recruit of the no oil exposure reference scenarios. The idea is to enable decision makers in spill areas, where an occurred spill resembles one of the hypothetical spills in this thesis, to quickly get a ballpark idea of the magnitude of future financial impacts. To get a more accurate prediction, the oil mortality model would have to be integrated into a population model that describes the local population under analysis. To illustrate this idea let us assume an oil accident has happened in Prince William Sound (PWS) (Table 6).

Oil type	Expected concentration of TPAH in water	Expected exposure time	Proportion of oiled coastline
Light fuel oil	*Mid*	*15 days*	*50 %*

Table 6, Characteristics of a hypothetical oil spill in PWS

According to Muradian et al. (2017), median of herring recruitment in PWS in 2013 was 35 million, and according to their results, herring in the area had most likely fallen below regulatory threshold. Therefore, let us assume initial population abundance to a low level according to the Ricker model parameterization used in the population model. The prediction model predicted, with similar oil spill characteristics in the Baltic Sea, an expected change of -0.003 Euros per recruit for total biomass, and around -0,0003 Euros per recruit for catches from the reference scenario. As a very rough estimate, the expected economic value decreases of this hypothetical oil spill in PWS, from the reference scenario level, would be -105000 Euros for total biomass and, if we assume similar proportional fishing mortalities as in the Baltic Sea scenario, -10500 Euros for catches. These estimated changes are much smaller than in the Baltic Sea scenario however, according to Muradian et al. (2017), estimated total biomass of herring in PWS was only about 10 000 tons compared to about 500 000 tons in the Baltic Sea, with the low population abundance used in the prediction model.

Estimating aspects of the Antonio Gramsci oil spill

As a very minor side task, the results of Rahikainen et al. (2017) were used for estimating aspects of the Antonio Gramsci 1987 oil spill. Because there was only one data point updating exposure time and concentration priors, their posteriors were mostly affected by the priors. It is, therefore, impossible to make any conclusions of the possible true concentration or exposure time of the spill. For this, more data points with, for example, results of estimated additional mortality as proportion would be needed.

The BMA model for assessing the possible oil type of the spill, was somewhat sensitive to the priors of concentration and exposure time parameters. It seems the model allocates probability to oil types, whose additional mortality characteristics, defined by the modified meta-analysis model, best fit the additional mortality of the Rahikainen et al. (2017) results, given the concentration and exposure time priors. The modified meta-analysis model results show ANSCO is the least lethal crude oil type of the data set followed by Prudhoe Bay crude oil (Table 4). The remaining three crude oils were quite similar however, Cook Inlet crude oil seems to be a little bit more lethal than Venezuela and Tuimaza crudes. Therefore, when the concentration and exposure time priors were changed from lower values to uniform or high values, the model allocated probability from the most lethal crude oil, Cook Inlet crude oil, to the least lethal crude oil, ANSCO. This makes sense, because the additional mortality results of the data point remained unchanged, but concentration and exposure time increased, and therefore the oil's induced additional mortality per exposure time must decrease. Even though changing the priors allocated probability to some extent between Cook Inlet crude oil and ANSCO, the most probable oil types were in all cases Venezuela crude oil and Tuimaza crude oil. It is good to note however, that even their probabilities were not very high, around 25 %.

Estimating these aspects was only a minor part of this thesis and it is hard to make any conclusions about them using only one data point. However, using the model developed for this thesis, makes it possible to assess unknown aspects related to any past spill, at least in a general level. The assessment would, however, need more data points for accuracy and possibly more parameters to explain the data points better.

Final conclusions

This thesis aimed at developing a model, with which it would be possible to predict oil spill impacts on Baltic Sea main basin herring population and furthermore, predict how these impacts on the population would economically impact fishermen. These aims were very well achieved. The prediction model developed in this thesis was able to predict oil spill impacts on both the Baltic Sea main basin herring population dynamics, and on the economic values of biomass and catches. The developed model is a great example of how data collected from laboratory studies can be integrated into population scale estimates.

Predictions made with the model can be used for risk assessment of possible future oil spills, and for decision analysis after an oil spill has happened. Furthermore, the estimation of the Antonio Gramsci 1987 spill aspects demonstrated the capability of the model to estimate unknown aspects of past spills. The economic impact predictions can function as bases for determining appropriate compensations to fishermen, and other possible stakeholders, after a spill has occurred. The model can be fitted to other fish populations and species by changing the population model parameters accordingly. In its present form, the model can offer rough estimates of impacts on other herring, and similar species, population dynamics and economic values in other areas, with the per recruit predictions of changes in values of catches and total biomass.

Many important areas of development were identified in the model. The oil mortality estimation part of the model could be extended to include more oils by adding more studies to the modified meta-analysis model. The main mortality causing characteristic of oil was assumed to be its weight however, there are other factors the modified meta-analysis model should consider. The accuracy of the results could be enhanced by including more studies with results of oil induced additional mortality per oil type. Furthermore, the data set used in the population model was the same as in Mäntyniemi et al (2013a), which is quite old and should be updated to a more recent time series.

According to the results, the prediction model is sensitive to the stock-recruitment relationship assumptions made in the population model. Future research should be directed to accurately estimate the true stock-recruitment relationship of Baltic Sea main basin herring, and the same applies to any fish population to which the model could be applied to.

The predicted changes in values made with the model, were only due to oil induced egg mortality. The prediction model developed in this thesis does not account for oil impacts on other life stages of herring, sublethal effects on herring, or damages to the environments where herring live and spawn. Therefore, the estimated financial impacts in this thesis should be considered only as one part of the possible total financial impacts, which could be estimated better if the model would consider the missing factors mentioned above. Furthermore, the calculation of the economic values should be developed to consider effects on prices from changes in supply and demand, and other possibly important factors.

As a conclusion, the bioeconomic prediction model developed in this thesis is a generic impact assessment and risk analysis tool for decision making, with which the prediction of both biological and economic impacts of oil on fish populations is possible. The model in its present form can be thought of as a first version, which can be updated, indefinitely even, by adding more parameters and adding knowledge and data from both laboratory and field to the latest parameter posteriors, by treating them as new priors. This is the Bayesian way.

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8 Appendices

APPENDIX 1. Raubenheimer et al. (unpublished) data set

Study	***Exposure time in days***	***Mortality proportion***	***Concentration in parts per million***	***Oil type***
1	*4*	*0,07*	*0,009*	*ANSCO*
1	*4*	*0,09*	*0,6*	*ANSCO*
1	*4*	*0,09*	*3*	*ANSCO*
1	*4*	*0,1*	*0,6*	*ANSCO*
1	*4*	*0,10*	*0,009*	*ANSCO*
1	*4*	*0,10*	*0,09*	*ANSCO*
1	*4*	*0,10*	*0,00001*	*ANSCO*
1	*4*	*0,1*	*0,00001*	*ANSCO*
1	*4*	*0,11*	*0,007*	*ANSCO*
1	*4*	*0,11*	*0,007*	*ANSCO*
1	*4*	*0,12*	*0,09*	*ANSCO*
1	*4*	*0,15*	*3*	*ANSCO*
2	*16*	*0,08*	*0,05*	*ANSCO*
2	*16*	*0,08*	*0,00001*	*ANSCO*
2	*16*	*0,10*	*0,01*	*ANSCO*
2	*8*	*0,06*	*0,005*	*ANSCO*
2	*8*	*0,07*	*0,05*	*ANSCO*
2	*8*	*0,08*	*0,01*	*ANSCO*
2	*16*	*0,18*	*0,08*	*ANSCO*
2	*16*	*0,20*	*0,005*	*ANSCO*
2	*8*	*0,11*	*0,08*	*ANSCO*
2	*8*	*0,11*	*0,00001*	*ANSCO*
3	*8*	*0,02*	*0,00001*	*ANSCO*
3	*8*	*0,03*	*0,00001*	*ANSCO*
3	*8*	*0,04*	*0,00023*	*ANSCO*
3	*8*	*0,04*	*0,00001*	*ANSCO*
3	*8*	*0,06*	*0,001*	*ANSCO*
3	*8*	*0,08*	*0,00013*	*ANSCO*
7	*11*	*0,00*	*0,121*	*ANSCO*
7	*11*	*0,00*	*1,210*	*ANSCO*
7	*11*	*0,00*	*1,040*	*ANSCO*

7	*11*	*0,01*	*12,10*	*ANSCO*
7	*11*	*0,01*	*1,370*	*ANSCO*
7	*11*	*0,01*	*0,1*	*ANSCO*
7	*11*	*0,02*	*0,137*	*ANSCO*
7	*11*	*0,02*	*1,040*	*ANSCO*
7	*11*	*0,02*	*0,1*	*ANSCO*
7	*11*	*0,03*	*1,210*	*ANSCO*
7	*11*	*0,026*	*13,70*	*ANSCO*
7	*11*	*0,03*	*0,00001*	*ANSCO*
7	*11*	*0,03*	*0,00001*	*ANSCO*
7	*11*	*0,03*	*1,040*	*ANSCO*
7	*11*	*0,04*	*0,1*	*ANSCO*
7	*11*	*0,04*	*0,137*	*ANSCO*
7	*11*	*0,04*	*10,40*	*ANSCO*
7	*11*	*0,05*	*1,210*	*ANSCO*
7	*11*	*0,05*	*0,121*	*ANSCO*
7	*11*	*0,05*	*0,00001*	*ANSCO*
7	*11*	*0,05*	*0,00001*	*ANSCO*
7	*11*	*0,05*	*0,00001*	*ANSCO*
7	*11*	*0,05*	*0,00001*	*ANSCO*
7	*11*	*0,06*	*0,1*	*ANSCO*
7	*11*	*0,06*	*0,121*	*ANSCO*
7	*11*	*0,06*	*0,137*	*ANSCO*
7	*11*	*0,06*	*1,210*	*ANSCO*
7	*11*	*0,06*	*0,121*	*ANSCO*
7	*11*	*0,07*	*1,040*	*ANSCO*
7	*11*	*0,07*	*10,40*	*ANSCO*
7	*11*	*0,08*	*0,00001*	*ANSCO*
7	*11*	*0,08*	*0,00001*	*ANSCO*
7	*11*	*0,09*	*10,40*	*ANSCO*
7	*11*	*0,09*	*1,370*	*ANSCO*
7	*11*	*0,09*	*1,370*	*ANSCO*
7	*11*	*0,10*	*13,70*	*ANSCO*
7	*11*	*0,14*	*12,10*	*ANSCO*
7	*11*	*0,17*	*0,00001*	*ANSCO*
7	*11*	*0,17*	*0,00001*	*ANSCO*
7	*11*	*0,22*	*0,137*	*ANSCO*
7	*11*	*0,30*	*0,00001*	*ANSCO*
7	*11*	*0,30*	*0,00001*	*ANSCO*
7	*11*	*0,41*	*1,370*	*ANSCO*
7	*11*	*0,59*	*12,10*	*ANSCO*
7	*11*	*0,83*	*10,40*	*ANSCO*
7	*11*	*0,85*	*12,10*	*ANSCO*

7	*11*	*0,85*	*13,70*	*ANSCO*
7	*11*	*0,97*	*13,70*	*ANSCO*
8	*16*	*0,00*	*0,0001*	*ANSCO*
8	*16*	*0,00*	*0,0007*	*ANSCO*
8	*16*	*0,05*	*0,00005*	*ANSCO*
8	*16*	*0*	*0,009*	*ANSCO*
8	*16*	*0,08*	*0,0004*	*ANSCO*
8	*16*	*0,09*	*0,002*	*ANSCO*
8	*16*	*0,17*	*0,008*	*ANSCO*
8	*16*	*0,20*	*0,00004*	*ANSCO*
8	*16*	*0,32*	*0,03*	*ANSCO*
8	*16*	*0,55*	*0,09*	*ANSCO*
4	*18*	*0,08*	*0,20000*	*Prudhoe Bay*
4	*18*	*0,14*	*0,10000*	*Prudhoe Bay*
4	*18*	*0,15*	*0,04000*	*Prudhoe Bay*
4	*18*	*0,17*	*0,00001*	*Prudhoe Bay*
4	*18*	*0,21*	*0,02000*	*Prudhoe Bay*
4	*18*	*0,24*	*0,00001*	*Prudhoe Bay*
4	*18*	*0,25*	*0,48000*	*Prudhoe Bay*
4	*18*	*0,27*	*0,00200*	*Prudhoe Bay*
4	*18*	*0,27*	*0,96000*	*Prudhoe Bay*
4	*18*	*0,30*	*1,94000*	*Prudhoe Bay*
4	*18*	*0,39*	*0,00001*	*Prudhoe Bay*
4	*1,5*	*0,28*	*1,94000*	*Prudhoe Bay*
4	*1,5*	*0,35*	*1,94000*	*Prudhoe Bay*
4	*1,5*	*0,37*	*0,00001*	*Prudhoe Bay*
4	*1,5*	*0,40*	*0,48000*	*Prudhoe Bay*
4	*1,5*	*0,40*	*0,48000*	*Prudhoe Bay*
4	*1,5*	*0,45*	*0,48000*	*Prudhoe Bay*
4	*1,5*	*0,50*	*1,94000*	*Prudhoe Bay*
4	*1,5*	*0,60*	*0,48000*	*Prudhoe Bay*
4	*1,5*	*0,65*	*1,94000*	*Prudhoe Bay*
10	*2*	*0,58*	*0,1*	*Prudhoe Bay*
10	*0,5*	*0,27*	*0,1*	*Prudhoe Bay*
10	*2*	*0,72*	*0,1*	*Prudhoe Bay*
10	*1*	*0,58*	*0,1*	*Prudhoe Bay*
10	*2*	*0,86*	*0,1*	*Prudhoe Bay*
10	*1*	*0,65*	*0,1*	*Prudhoe Bay*
10	*0,5*	*0,42*	*0,1*	*Prudhoe Bay*
10	*0,17*	*0,17*	*0,002*	*Prudhoe Bay*
10	*6*	*0,9999*	*0,1*	*Prudhoe Bay*
10	*6*	*0,9999*	*0,1*	*Prudhoe Bay*
10	*6*	*0,9999*	*0,1*	*Prudhoe Bay*

10	1	0,80	0,1	Prudhoe Bay
10	0,33	0,49	0,1	Prudhoe Bay
10	0,5	0,70	0,1	Prudhoe Bay
10	0,33	0,56	0,1	Prudhoe Bay
10	0,33	0,65	0,1	Prudhoe Bay
10	0,17	0,44	0,1	Prudhoe Bay
10	0,17	0,45	0,1	Prudhoe Bay
10	0,17	0,51	0,1	Prudhoe Bay
10	0,17	0,61	0,002	Prudhoe Bay
10	0,17	0,61	0,002	Prudhoe Bay
5	6	0	0,00001	Venezuela
5	6	0,02	0,00001	Venezuela
5	6	0,08	0,1	Venezuela
5	6	0,09	1	Venezuela
5	6	0,26	10	Venezuela
6	6	0	0,1	Venezuela
6	6	0	0,00001	Venezuela
6	6	0,02	0,1	Venezuela
6	6	0,08	0,1	Venezuela
6	6	0,08	1	Venezuela
6	6	0,10	1	Venezuela
6	6	0,12	1	Venezuela
6	6	0,27	10	Venezuela
6	6	0,28	10	Venezuela
6	6	0,30	1	Venezuela
6	6	0,49	10	Venezuela
9	12	0,15	0,8	cook inlet
9	12	0,20	0,00001	cook inlet
9	12	0,25	1	cook inlet
9	12	0,41	1	cook inlet
9	2	0,20	2	cook inlet
9	12	0,75	2	cook inlet
9	2	0,21	2	cook inlet
9	2	0,21	5	cook inlet
9	2	0,22	4	cook inlet
9	2	0,25	0,00001	cook inlet
9	12	0,9999	3	cook inlet
9	12	0,9999	3	cook inlet
9	12	0,9999	4	cook inlet
6	6	0,03	1	Tuimaza
6	6	0,03	0,00001	Tuimaza
6	6	0,08	0,1	Tuimaza
6	6	0,08	1	Tuimaza

6	*6*	*0,15*	*1*	*Tuimaza*
6	*6*	*0,17*	*10*	*Tuimaza*
6	*6*	*0,21*	*1*	*Tuimaza*
6	*6*	*0,22*	*0,1*	*Tuimaza*
6	*6*	*0,24*	*10*	*Tuimaza*
6	*6*	*0,26*	*0,1*	*Tuimaza*
6	*6*	*0,33*	*10*	*Tuimaza*
11	*3*	*0,10*	*5*	*benzene*
11	*3*	*0,15*	*18*	*benzene*
11	*2*	*0,15*	*5*	*benzene*
11	*2*	*0,15*	*18*	*benzene*
11	*3*	*0,27*	*45*	*benzene*
11	*1*	*0,10*	*5*	*benzene*
11	*1*	*0,12*	*18*	*benzene*
11	*2*	*0,27*	*45*	*benzene*
11	*1*	*0,15*	*0,00001*	*benzene*
11	*1*	*0,27*	*45*	*benzene*
3	*8*	*0,02*	*0,00062*	*heavy fuel*
3	*8*	*0,03*	*0,00001*	*heavy fuel*
3	*8*	*0,05*	*0,00027*	*heavy fuel*
3	*8*	*0,07*	*0,00001*	*heavy fuel*
3	*8*	*0,09*	*0,002*	*heavy fuel*
3	*8*	*0,10*	*0,00062*	*heavy fuel*
3	*8*	*0,13*	*0,001*	*heavy fuel*
3	*8*	*0,17*	*0,0011*	*heavy fuel*
6	*6*	*0,01*	*0,05*	*light fuel*
6	*6*	*0,09*	*0,5*	*light fuel*
6	*6*	*0,30*	*0,5*	*light fuel*
6	*6*	*0,36*	*0,05*	*light fuel*
6	*6*	*0,39*	*0,5*	*light fuel*
6	*6*	*0,40*	*0,05*	*light fuel*
6	*6*	*0,96*	*0,5*	*light fuel*
6	*6*	*0,9999*	*5*	*light fuel*
6	*6*	*0,9999*	*5*	*light fuel*
6	*6*	*0,9999*	*5*	*light fuel*

APPENDIX 2. Code of the modified meta-analysis model

```
jags_model_code="model{
#Below is the model for Raubenheimer et al. data set
############################################################3
for(i in 1:n){  # loop through all observations
# linear Gaussian model for the log-survival (ls[i])
x[i]~dnorm(mu[i],pow(sigma,-2))
pred_x[i]~dnorm(mu[i],pow(sigma,-2))
pred_surv[i] = exp(-exp(pred_x[i]) * exposuretime[i])
Bayesian_p_value[i]=step(x[i]-pred_x[i])
mu[i]<-log(exp(alpha[study[i]])+exp(M[oil_type[i]])*exposure[i]*(log(concentration[i]+0.000000001)+12))
}
# #Below is the code for Rahikainen et al. data point
# #######################################################################

x[n+1]~dbin(pred_survadd,N)
pred_x[n+1]~dbin(pred_survadd,N)
pred_survaddp~dnorm(muadd[mucat],pow(sigma,-2))
pred_survadd=exp(-exp(pred_survaddp))
pred_mortadd = 1-pred_survadd
for(i in 1:5){
  muadd[i]<-log((exp(M[i])*(log(concentration2+0.000000001)+8))*exposuretime2)  # M:  additional  mortality rate due to exposure, alpha: baseline mortality rate in control group = mean mortality effect mu
}
###########################################################################################
##### Examples of the effect of oil type specific additional IMOLS per exposure time parameters on mortality
for(i in 1:8){
pred_survaddexample[i]~dnorm(muaddexample[i],pow(sigma,-2))
pred_mortaddexample[i]= 1 - exp(-exp(pred_survaddexample[i]))
muaddexample[i] <- log((exp(M[i])*(log(0.1+0.000000001)+8))*15)
}
###########################################################################################
##### Examples of the effect of IMOLS per exposure time with no exposure parameters on mortality
for(i in 1:11){
pred_survalphaexample[i]~dnorm(mualphaexample[i],pow(sigma,-2))
```

```
pred_mortalphaexample[i]= 1 - exp(-exp(pred_survalphaexample[i])*15)
mualphaexample[i] <- log(exp(alpha[i]) + exp(M[3])*(log(0.02+0.000000001)+12))
}
##priors for hyperparameters of oil type specific additional IMOLS per exposure time
##########################################################################################
for(i in 1:8){
  M[i] ~ dnorm(muMalloils + (APIeffect*(API[i]-commonpopAPI)), pow(STDoilclass, -2)) #EVO/ANSCO
}
muMalloils ~ dnorm(0, pow(10, -2)) #T(0,1)
STDoilclass ~ dunif(0.01, 50)
commonpopAPI ~ dnorm(32.7, pow(15,-2))
APIeffect~dnorm(0,pow(1,-2))

API[1]=28  #EVO/ANSCO  #Different Ms for different oil types
API[2]=27   #Prudhoe
API[3]=31.14   #Venezuela
API[4]=35   #Cook Inlet
API[5]=33   #Tuimaza
API[6]=32.7   #Benzene
API[7]=13   #heavy fuel
API[8]=43   #light fuel

#Priors for hyperparameters of IMOLS per exposure time with no exposure
################################################################################33
for(i in 1:11){
  alpha[i]~dnorm(mualpha,pow(STDalpha, -2)) # different alphas for different studies
}
mualpha ~ dnorm(0, pow(10, -2))
STDalpha ~ dunif(0.01, 10)
#Rest of the priors
####################################################################################
mucat ~dcat(pmu[1:5])
pmu[1] <- 1/5
pmu[2] <- 1/5
pmu[3] <- 1/5
pmu[4] <- 1/5
pmu[5] <- 1/5
sigma~dunif(0.01,10)

concentration2~dnorm(0.006,pow(0.04,-2)) T(0.001,) #concentration parameter for Rahikainen et al data point
```

```
exposuretime2~dnorm(15,pow(4,-2)) T(0.001,)    #exposuretime parameter for Rahikainen et al data point

}" #JAGS model ends here
```

APPENDIX 3. Code of the additional oil type specific mortality block in the prediction model

```
################################################################
# Oil mortality model
################################################################

pph~dnorm(250,pow(5,-2))   #parameter for first sale price of herring

######Different oiled coastline proportions for scenarios
#OiledCl=0
#OiledCl~dbeta(0.9,6)       #10%
OiledCl~dbeta(5.5,6)       #50%
#OiledCl~dbeta(6,0.1)       #100%
#######

pred_addp~dnorm(muadd[mucat],pow(sigma,-2))      #predicted additional oil type specific IMOLS
pred_survadd = exp(-exp(pred_addp))              #transformation to proportion
pred_mortadd=1-pred_survadd                      #predicted additional mortality as a proportion

sigma<-pmvn[9]                                   #stadard deviation of additional IMOLS

for(i in 1:8){
  muadd[i]<-log((exp(OilM[i])*(log(concentration+0.000000001)+8))*exposuretime)
}

for(i in 1:8){
  OilM[i] <- pmvn[i]
}

#######Different concentrations for scenarios

# concentration~dnorm(0.006, pow(0.002,-2)) T(0.001,)        # ANCSCO lowC
# concentration~dnorm(0.02, pow(0.002,-2)) T(0.001,)         # ANCSCO midC
# concentration~dnorm(0.04, pow(0.002,-2)) T(0.001,)         # ANCSCO highC
# concentration~dnorm(0.02, pow(0.002,-2)) T(0.001,)         # Light fuel lowC
# concentration~dnorm(0.05, pow(0.002,-2)) T(0.001,)         # Light fuel midC
 concentration~dnorm(0.12, pow(0.002,-2)) T(0.001,)          # Light fuel highC

#################
```

```
exposuretime~dnorm(15, pow(4,-2)) T(0.001,)

mucat ~dcat(pmu[1:8])        #You can change the oil type according to the scenarios by assigning the probability of the oil type to 1
pmu[1] <- 0
pmu[2] <- 0
pmu[3] <- 0
pmu[4] <- 0
pmu[5] <- 0
pmu[6] <- 0
pmu[7] <- 0
pmu[8] <- 1

pmvn[1:n] ~ dmnorm.vcov(meanvec[1:n,1], covmat[1:n,1:n])
################################################################
```

APPENDIX 4. Development of the cumulative value changes from the reference scenario year by year for each prediction scenario

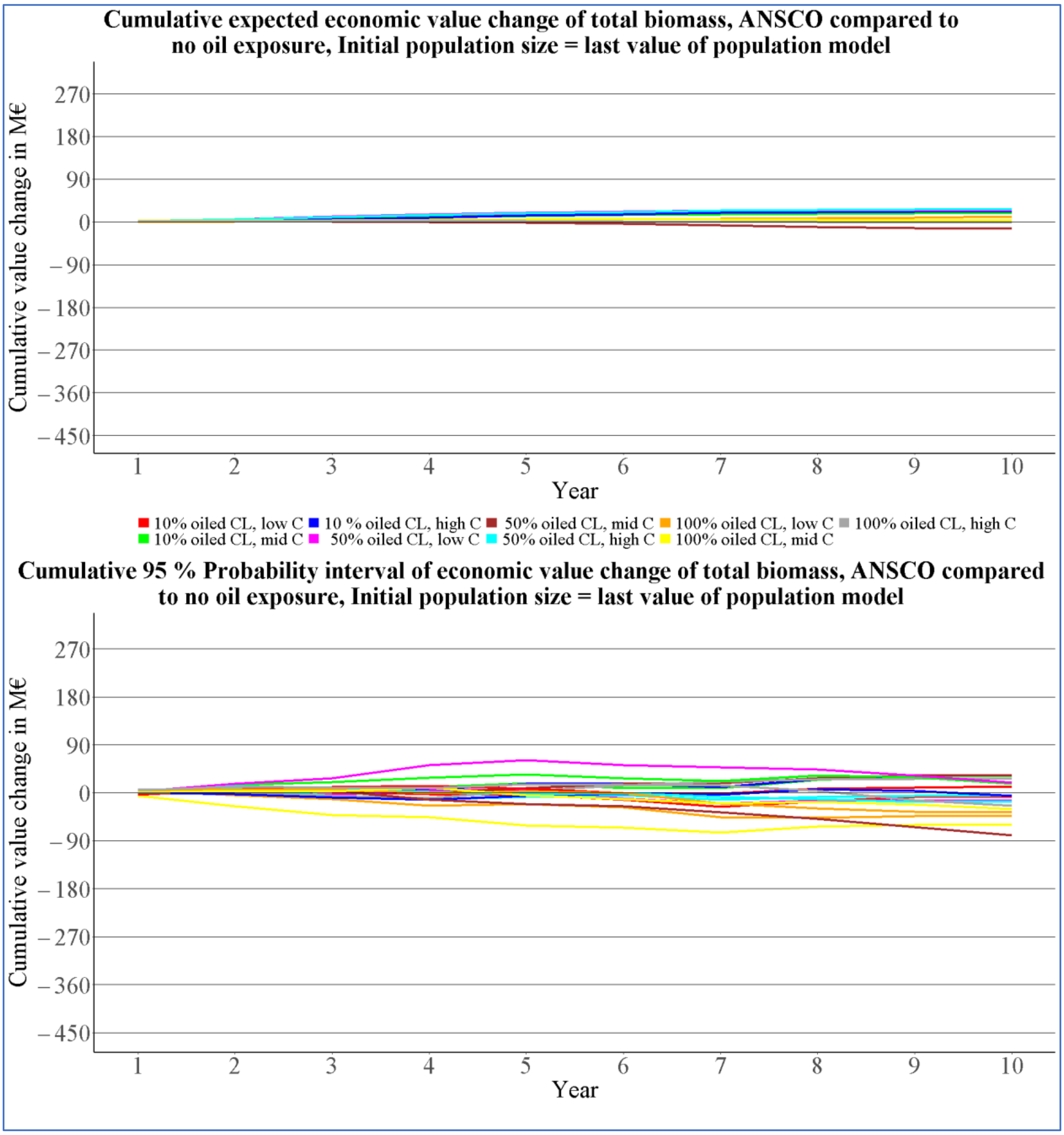

Figure 43, Prediction results: ANSCO, Initial population state = last value of population model

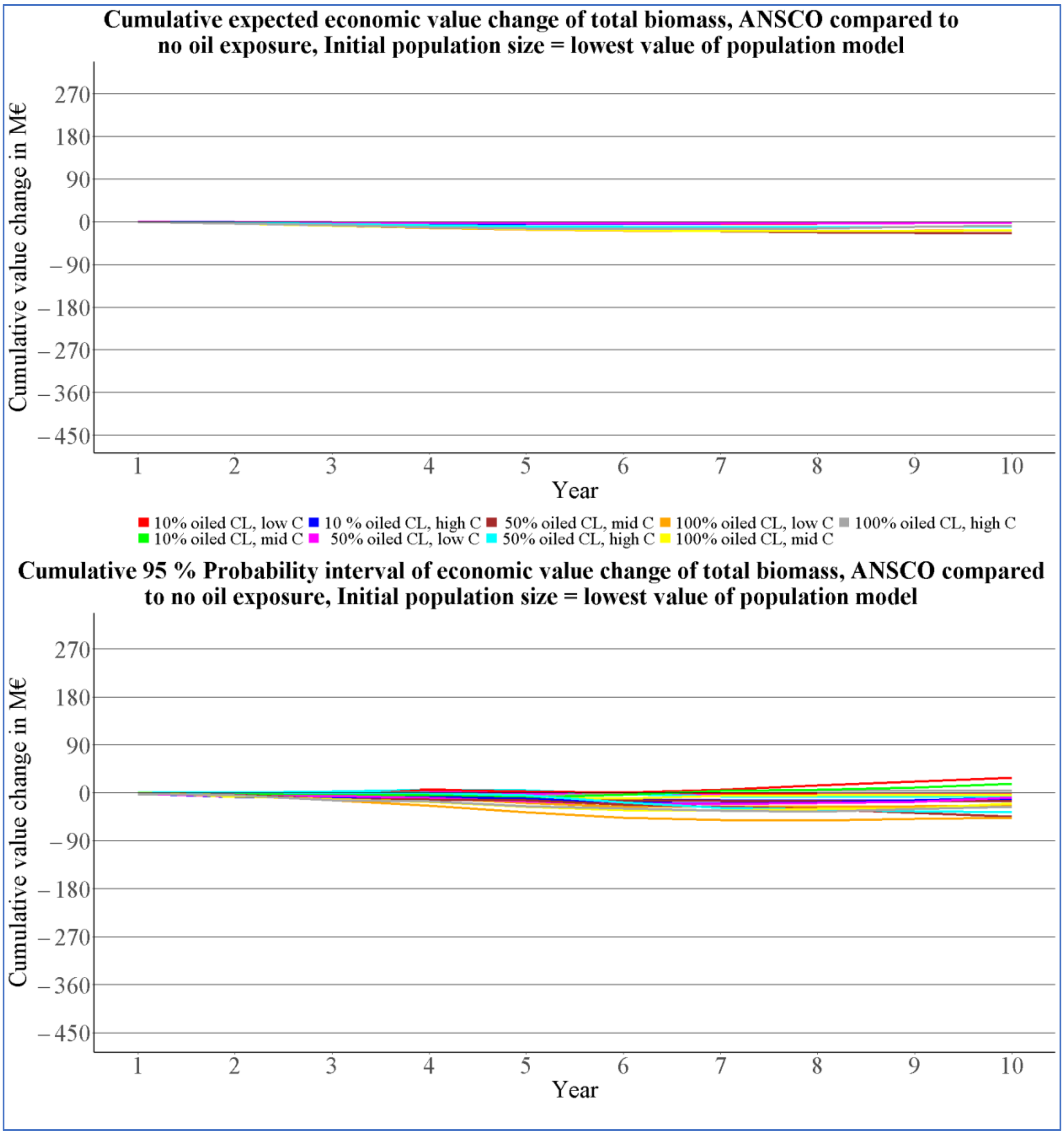

Figure 44, Prediction results: ANSCO, Initial population state = lowest value of population model

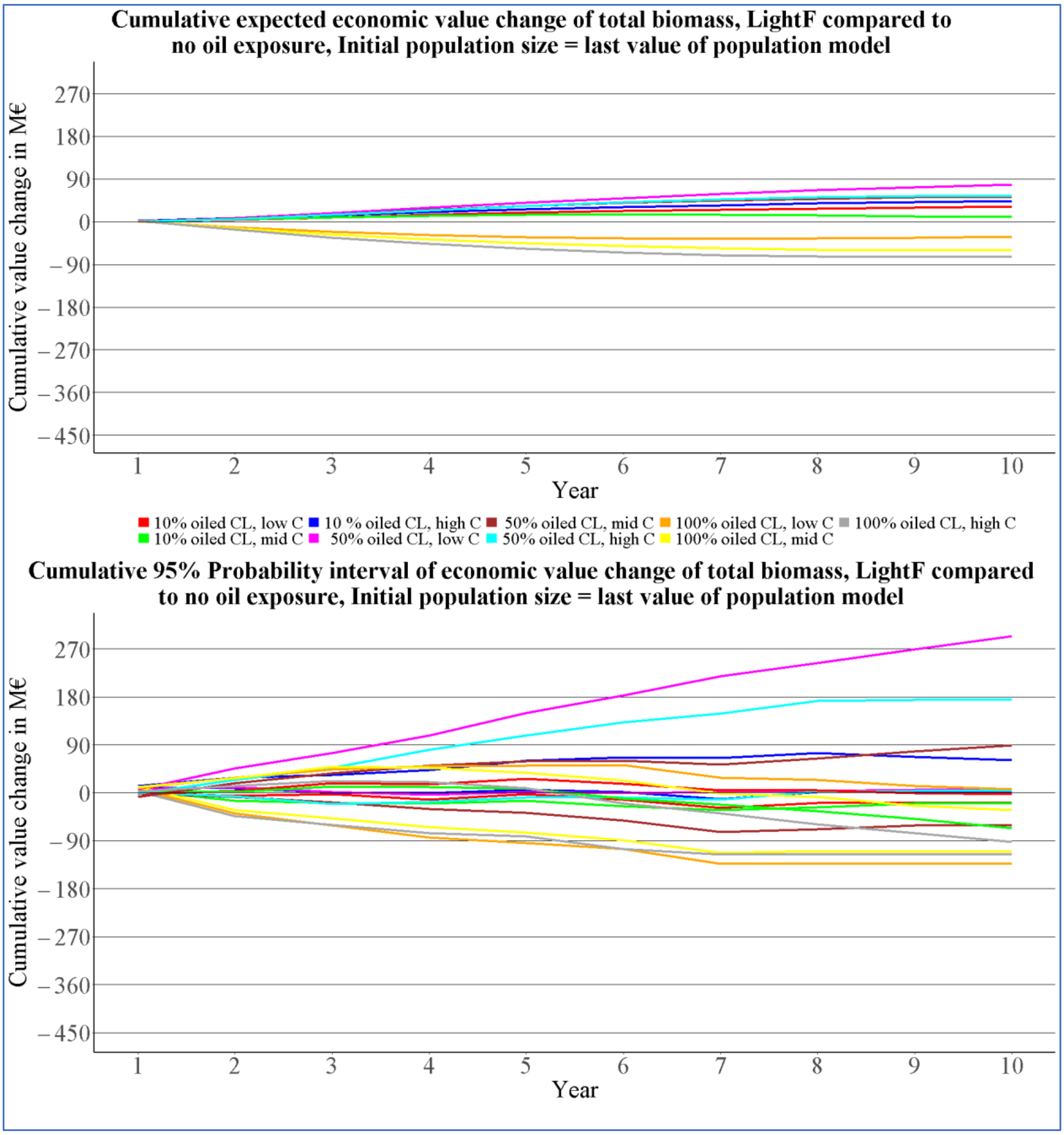

Figure 45, Prediction results: Light fuel oil, Initial population state = last value of population model

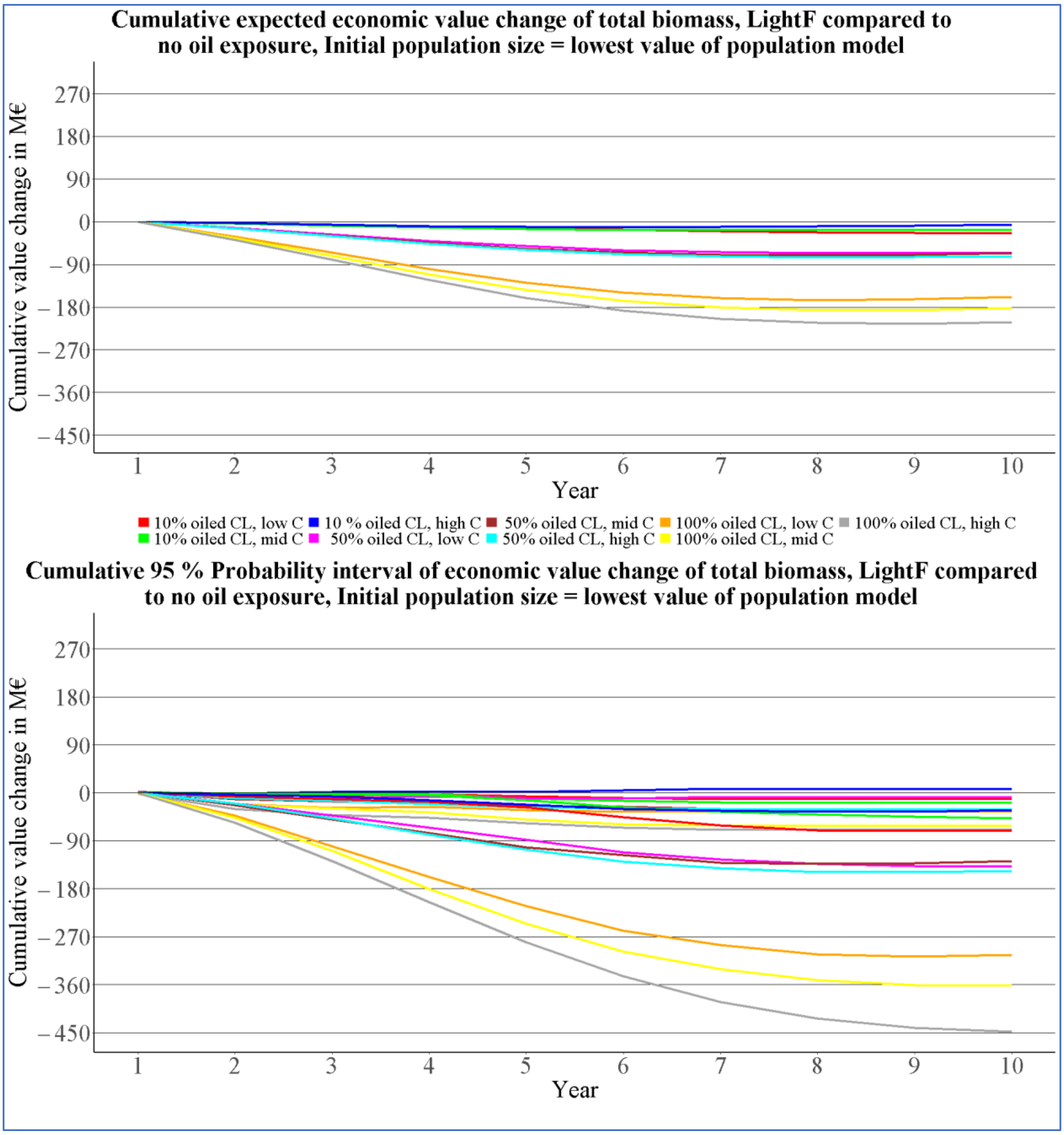

Figure 46, Prediction results: Light fuel oil, Initial population state = lowest value of population model

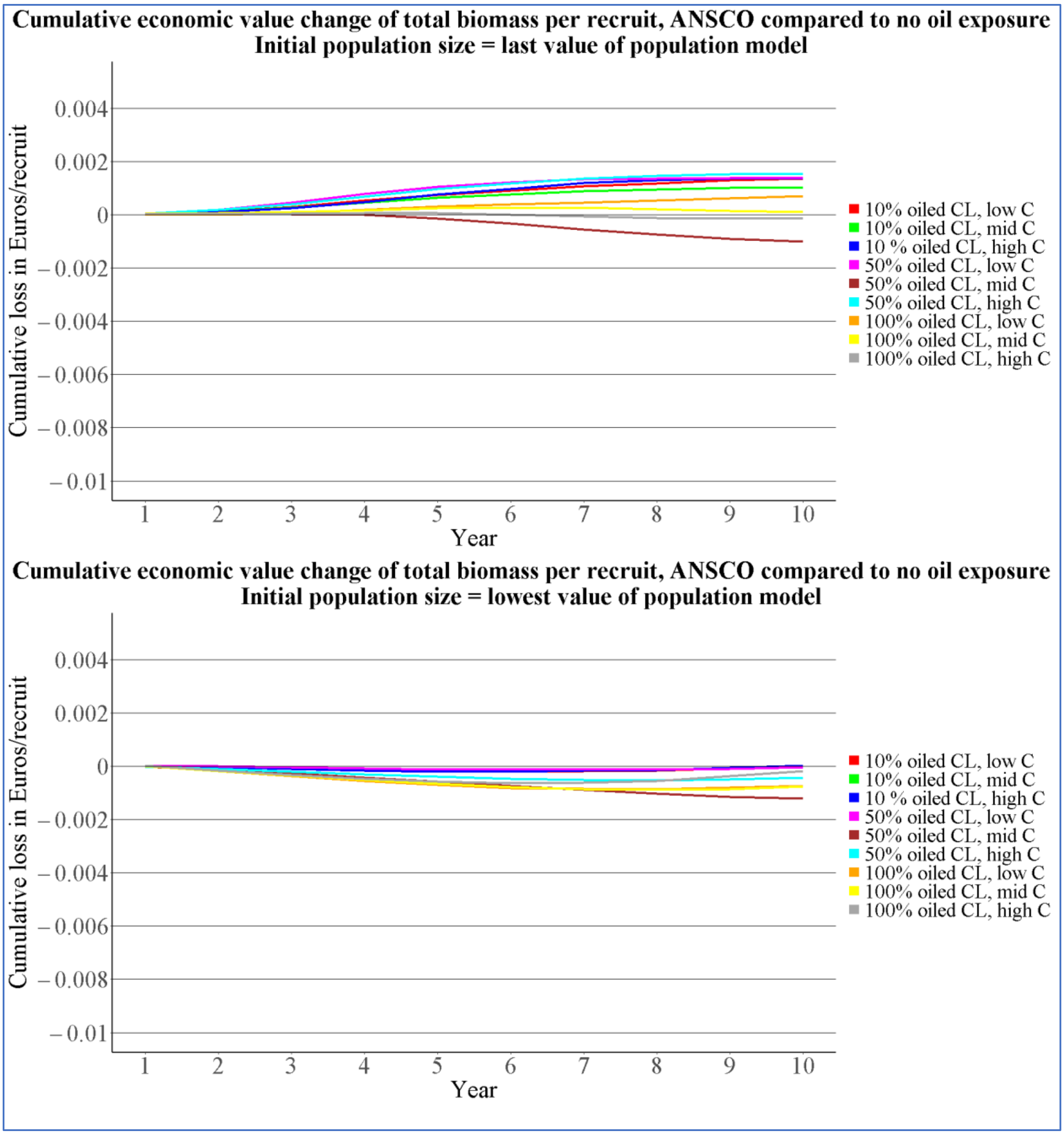

Figure 47, Prediction results: ANSCO, cumulative financial loss of total biomass per recruit

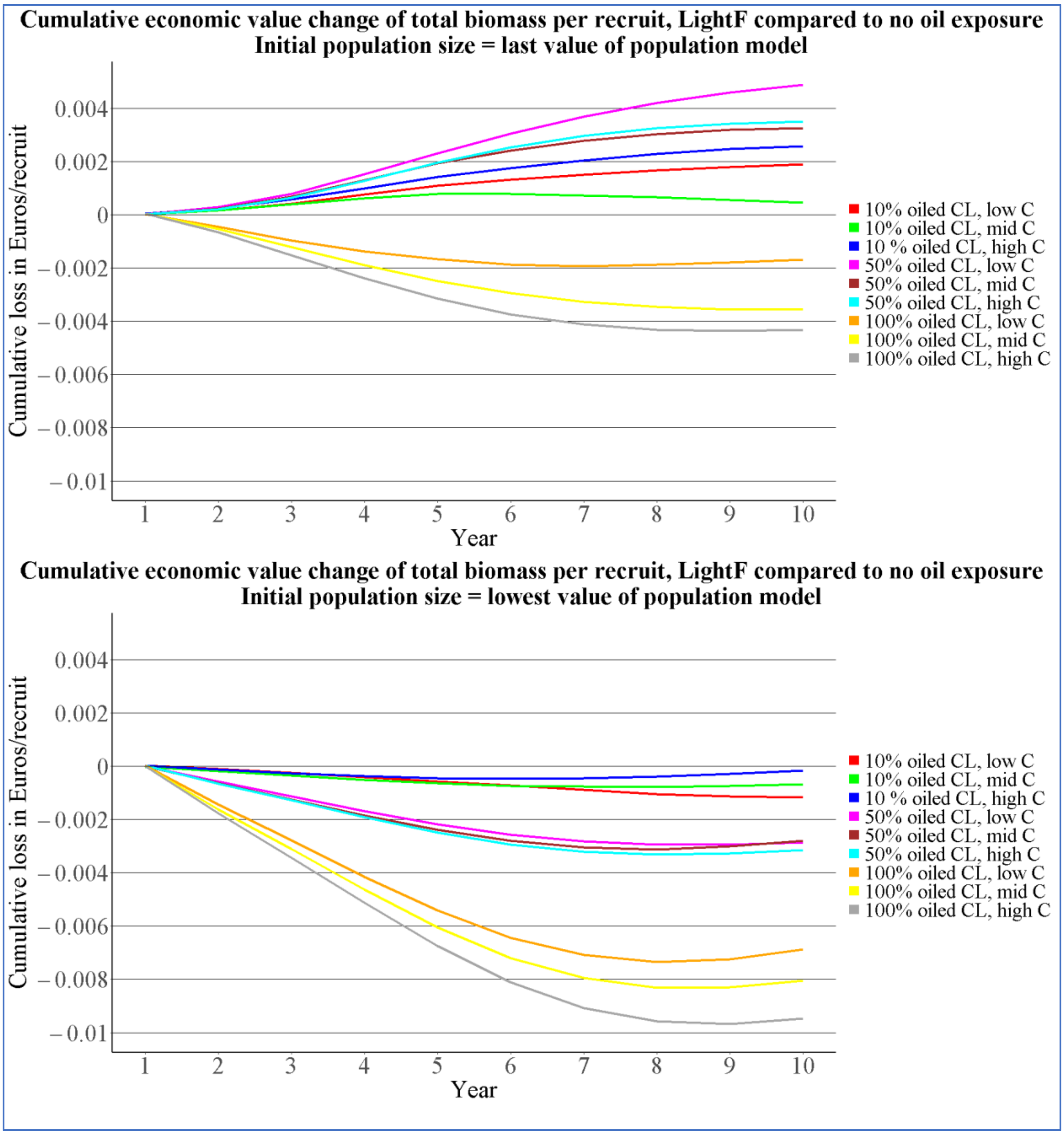

Figure 48, Prediction results: Light fuel oil, cumulative financial loss of total biomass per recruit

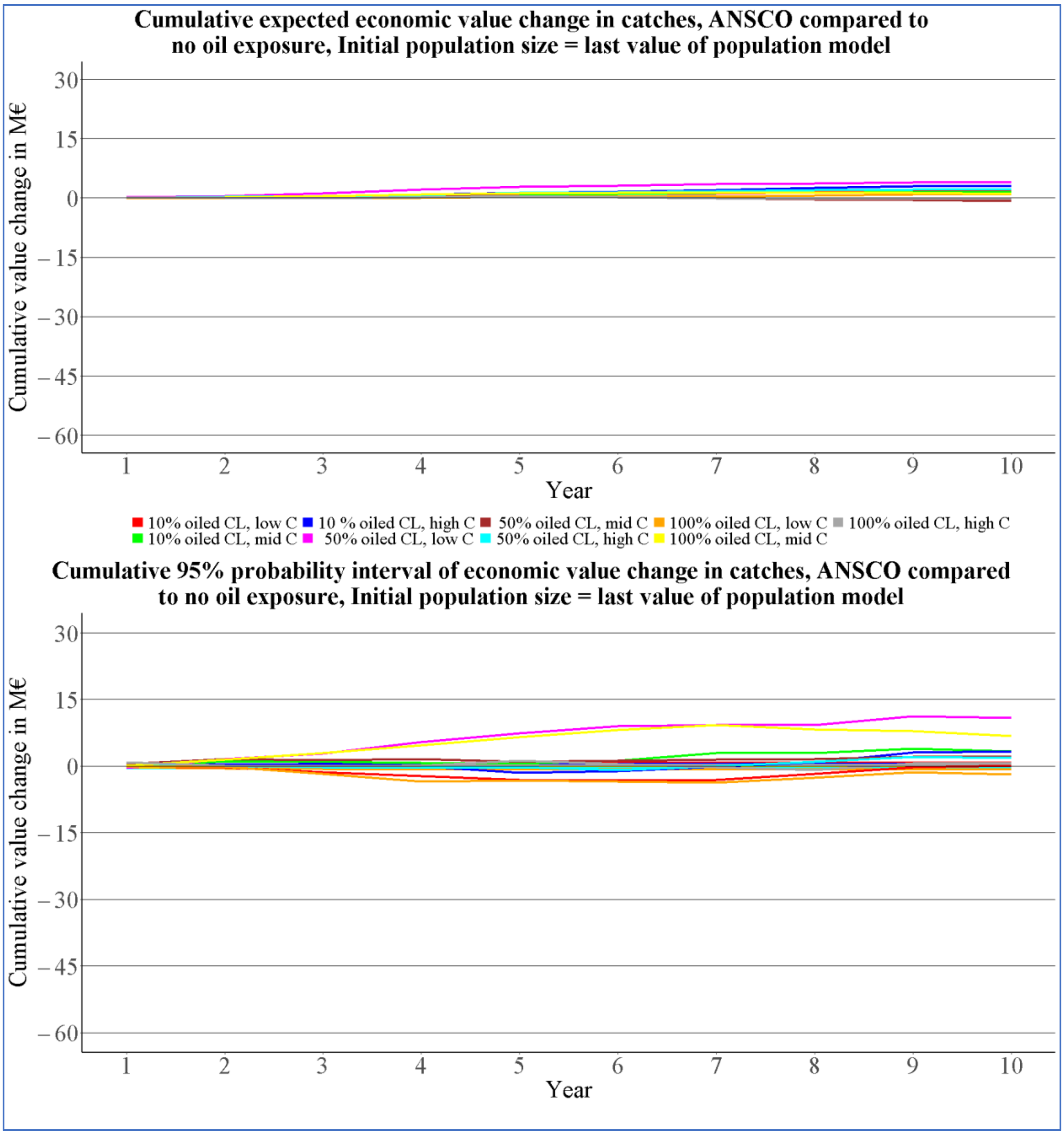

Figure 49, Prediction results: ANSCO, Initial population state = last value of population model

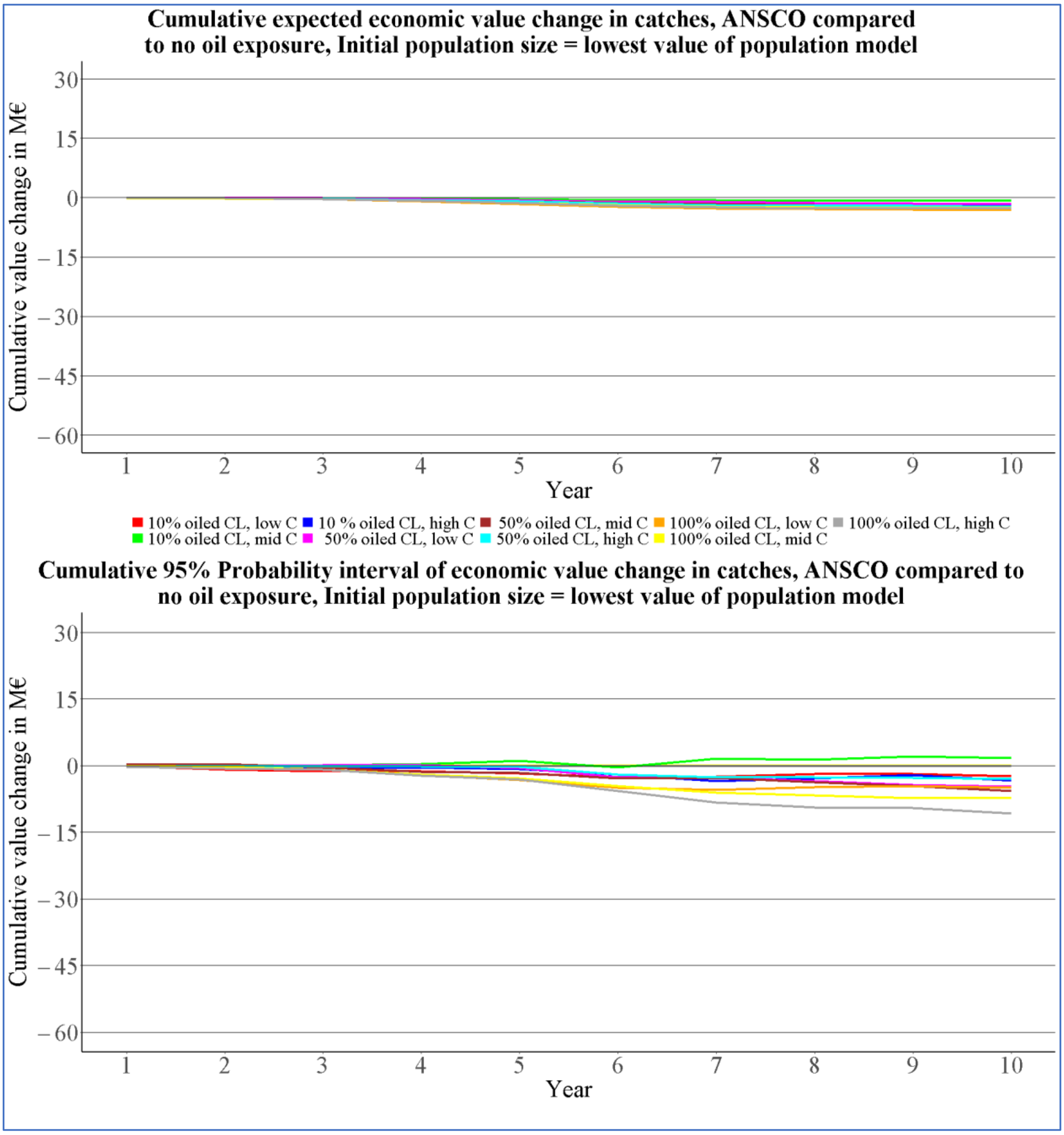

Figure 50, Prediction results: ANSCO, Initial population state = lowest value of population model

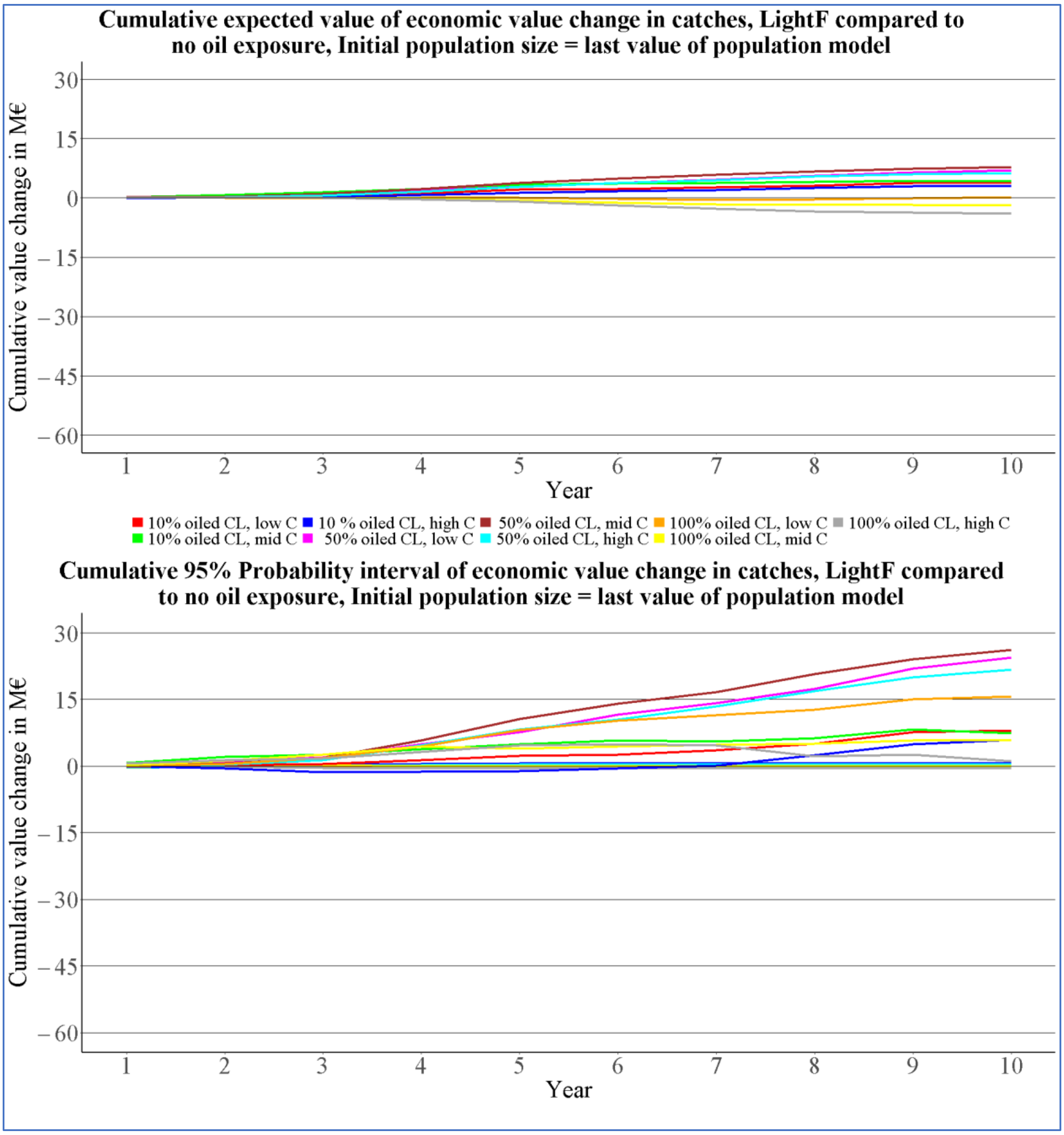

Figure 51, Prediction results: Light fuel oil, Initial population state = last value of population model

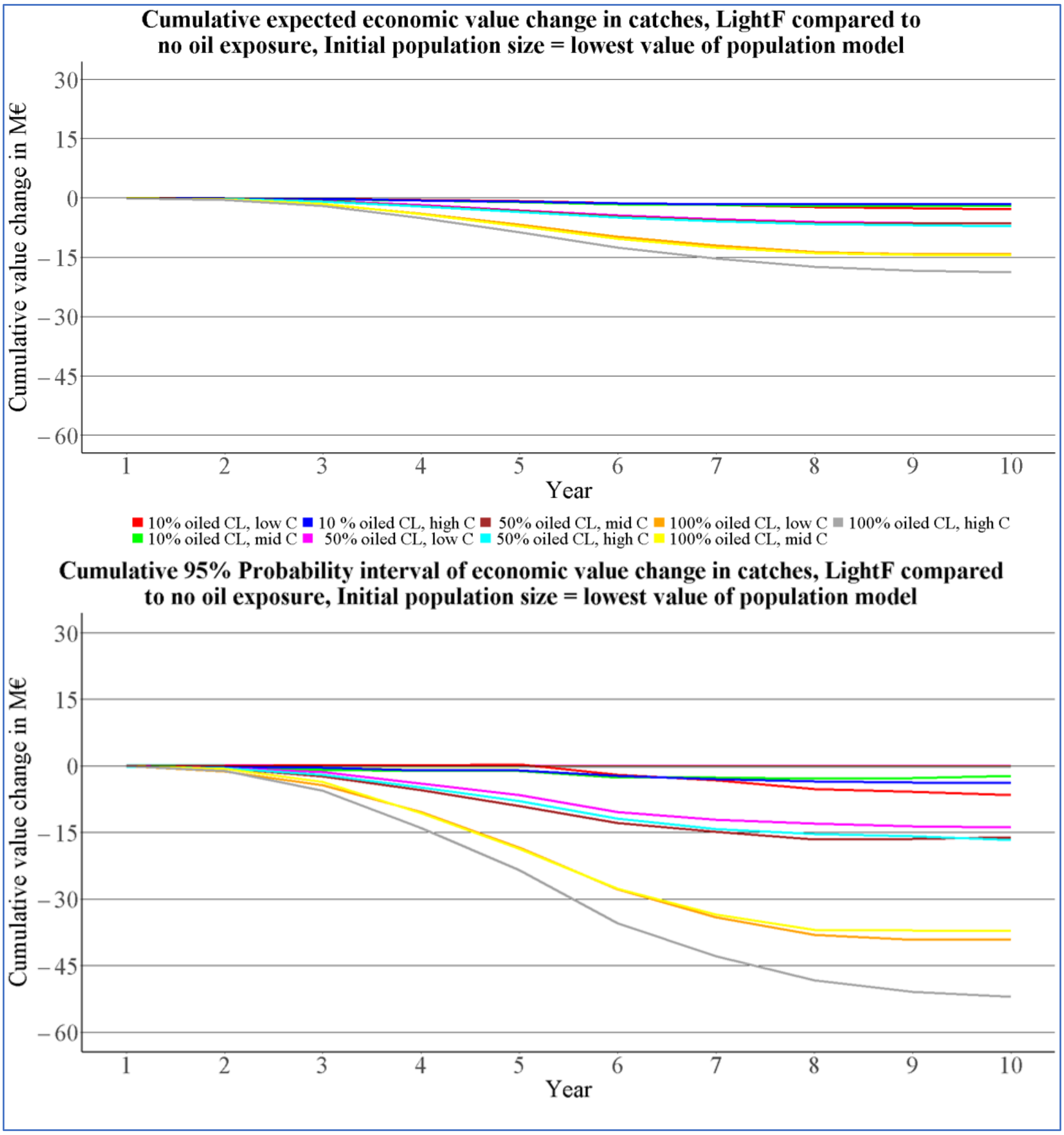

Figure 52, Prediction results: Light fuel oil, Initial population state = lowest value of population model

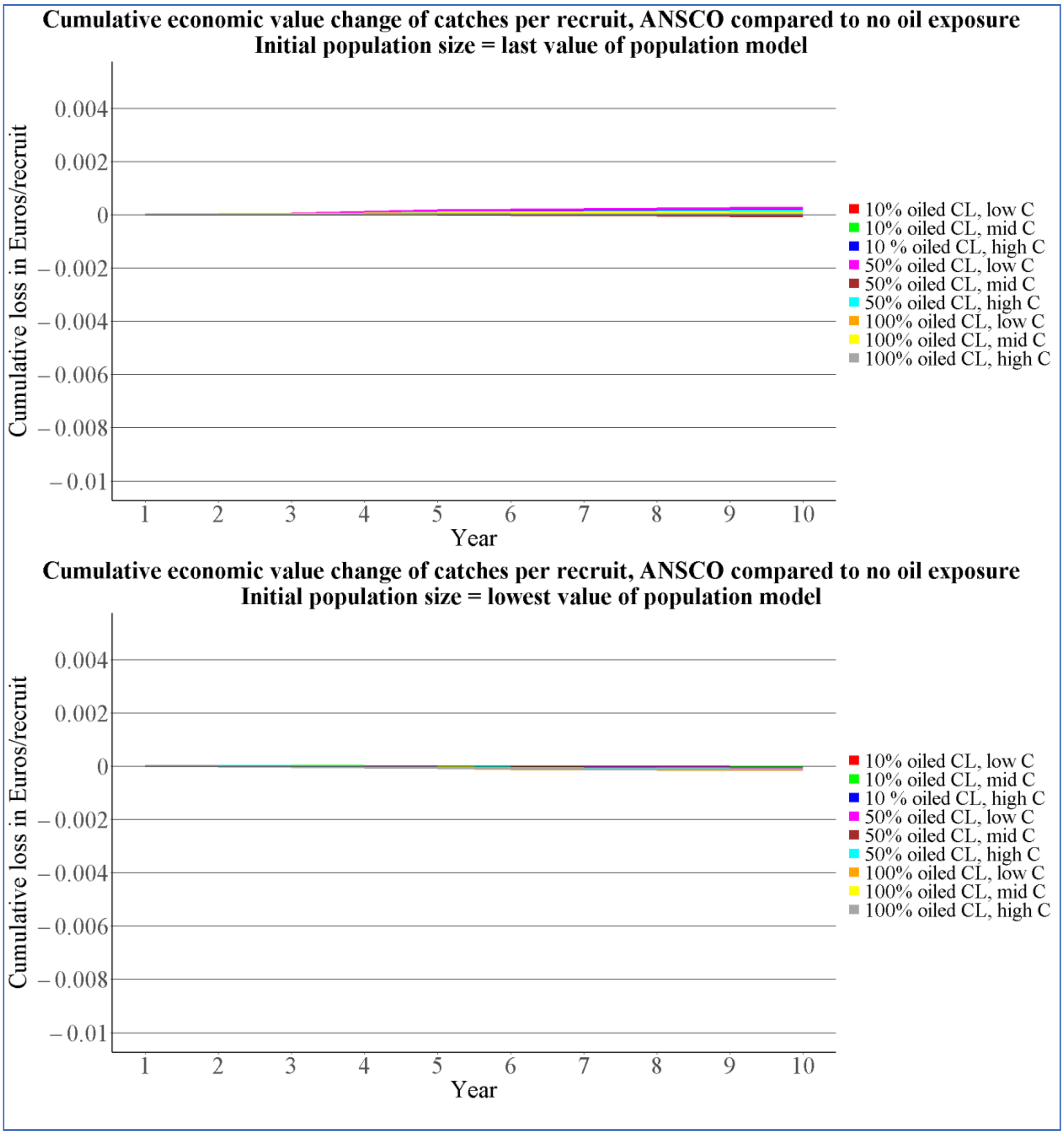

Figure 53, Prediction results: ANSCO, cumulative financial loss of catches per recruit

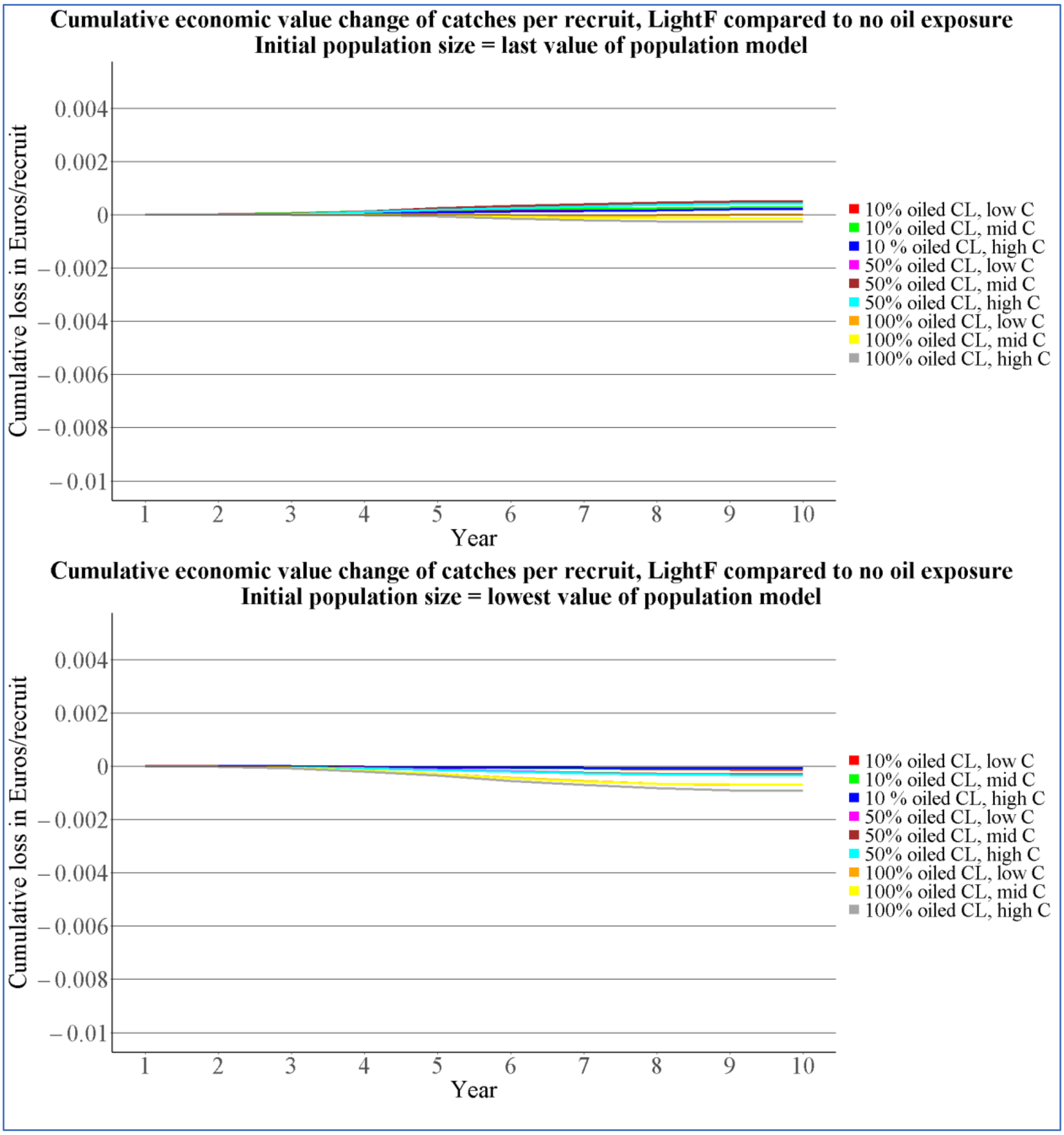

Figure 54, Prediction results: Light fuel oil, cumulative financial loss of catches per recruit