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Steps towards comprehensive Bayesian decision analysis in fisheries and environmental management

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ACADEMIC DISSERTATION

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To the memory of my brother Jussi

1987 – 2010

Contents

List of original publications

I Juntunen, T., Rosqvist, T., Rytkönen, J. & Kuikka, S., 2005. How to model the oil combatting technologies and their impacts on ecosystem: a Bayesian networks application in the Baltic Sea. *ICES CM 2005*/S:02.

II Juntunen, T., Vanhatalo, J., Peltonen, H. & Mäntyniemi, S., 2012. Bayesian spatial multispecies modeling to assess pelagic fish stocks from acoustic and trawl survey data. *ICES Journal of Marine Science* 69: 95-104.

III Juntunen, T., Tsikliras, A., Mäntyniemi, S. & Stergiou, K., 2013. A Bayesian population model to estimate changes in a stock size in data poor cases using Mediterranean bogue (*Boops boops*) and picarel (*Spicara smaris*) as an example. *Submitted.*

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V Juntunen, T., Hoviniemi, K-M. & Mäntyniemi, S., 2013. A Bayesian value of information analysis for common octopus (*Octopus vulgaris*) fishery management. *Manuscript*.

Author's contribution

I Mr. Juntunen was solely responsible for model structure, development and analysis. Dr. Rosqvist participated in writing. The original idea for the paper came from Prof. Kuikka.

II Mr. Juntunen coordinated the study, provided general model structure, assembled data sets and interpreted results. Dr. Vanhatalo implemented the model and Dr. Peltonen provided survey data sets. All three participated equally in writing. The original idea for the paper came from Prof. Mäntyniemi.

III Mr. Juntunen built the model and mainly wrote the article. Dr. Tsikliras and Prof. Stergiou provided data, commented, and wrote minor parts of the manuscript. Prof. Mäntyniemi provided ideas on model construction and wrote part of the discussion.

IV Mr. Juntunen analyzed data, built the model, and interpreted results. Ms. Ahtiainen provided the data and expert assistance in defining the problem field. Prof. Mäntyniemi supported model development by providing ideas. Mr. Juntunen was mainly responsible for writing with considerable support from both Ms. Ahtiainen and Prof. Mäntyniemi.

V Mr. Juntunen was responsible for the analysis, results and writing of the article. Mrs. Hoviniemi provided simulated data. Prof. Mäntyniemi wrote the description of the simulation model. The original idea for the paper came from Prof. Mäntyniemi.

Abstract

A typical decision problem in an environmental field includes a complex system with countless uncertain factors of both nature and human behavior. There are many stakeholders with conflicting objectives and a lot of decision alternatives, and results need to be communicated clearly to decision makers and stakeholders. Organized analysis is needed to tackle these challenges. In an ideal situation, we should analyze the objectives of every stakeholder and the responses from different parts of the ecosystem within one framework, which integrates the expertise and efforts of many different disciplines. Bayesian inference, especially the influence diagram, is a perfect tool to be used in such decision problems.

The main contribution of this thesis is in developing methods for the modeling of uncertainties in environmental decision problems. The focus is on having more complete decision analyses where more uncertainties are realistically modeled. By including more stochastic variables in the analysis, the decision makers get a more realistic picture of the uncertainties involved and can account for them in the decision making. The thesis consists of five separate research articles, which all contribute to the different parts of the Bayesian decision process presented in this summary. The process is divided into four steps: (1.) building a decision model, (2.) data gathering and processing, (3.) using the model, and (4.) post analysis. The summary presents the research articles and their contributions and critically reviews the tools and methods needed in the process.

The articles include a model for oil spill management, a spatial multispecies stock assessment model, a model for the stock assessment of data-poor species, a model to estimate uncertainties in environmental valuation and an influence diagram for value of information analysis. The methods used cover many aspects of the Bayesian decision process, outlining the problem, different ways to define prior distributions, utility functions, and finding maximum utility policies and value of information analysis. Hence, the tools used are diverse, too. In the models, I have used graphical Bayesian networks, numerical MCMC estimation, and Gaussian processes.

In conclusion, the results found in this thesis are small but important steps toward better and more comprehensive Bayesian decision analyses in environmental and fisheries management. They show that significant uncertainties exist in many parts of the system. Another important factor was the cooperation of scientists from many different disciplines with a variety of backgrounds, which is needed in the modeling of complex environmental problems.

1 Introduction

Decision analysis as a field of science was founded by Ronald Howard (1966). According to his definition it combines system analysis, decision theory, epistemic probability, and cognitive psychology. The aim of decision analysis is to provide guidance and information to decision makers and thus lead to better and more justified decisions. In complex systems there are no certain outcomes, thus there arose a need for a probabilistic approach to decision analysis. Howard Raiffa (1968) was the first to formally define Bayesian decision analysis, which consists of evaluation of different alternatives in terms of utilities and uncertainty.

Why Bayesian decision analysis? To put it simply, Bayesian inference is about updating a prior belief in light of new evidence. It is learning from experience. It sounds like a very reasonable and logical thing to do. Every time we observe something new, our previous belief about that observation is updated. The more observations we make, the more certain we can be about the underlying unobserved phenomenon. In fact, Bayesian inference can be used to describe how infants learn (Gopnik, 2012), and to model a human decision process (Glymour, 2001). Especially suitable Bayesian inference is for situations where there is no data available or where we cannot do repeated experiments. Under the frequentist paradigm it is impossible to define probability without these. In the environmental field there are many cases where we are predicting something that has not happened ever before. We must resort to subjective probabilities.

The history of Bayesian inference starts from the mid-18th century. It was then when Reverend Thomas Bayes came up with his famous rule. His findings were published posthumously in 1763 (Bayes & Price, 1763) and the theory was brought to its present form by Pierre-Simon Laplace (1774). Since then, Bayes' rule—the theory of inverse probability—remained unused for a long time. At the first half of the 20th century it was found again and the theory was improved by several scientists (e.g., de Finetti, 1931; Ramsey, 1931; Savage, 1954). At the same time, it was used in urgent real-life problems that needed solving, where conventional methods could not be applied. Already in the late 19th century, Russia and France used Bayes' rule to improve the hit rate of their artillery, and at the beginning of the 20th century it was used to route telephone calls and set insurance rates. During and after World War II, Bayes' rule was used in military operations to decipher coded messages and to optimize search patterns. That was a significant turning point and since then Bayesian inference has steadily gained more footholds in many disciplines (McGrayne, 2011).

As history shows, Bayes' rule has always been used to solve practical decision problems. However, the founder of both modern Bayesian decision theory and decision analysis is Howard Raiffa (Schlaifer, 1959; Raiffa & Schlaifer, 1961; Raiffa, 1968; Pratt et al., 1995). The early 1970s was the time when Bayesian decision theory started booming in many fields, including engineering, economics and medicine (Gremy et al., 1969; Benjamin, 1970; Martz & Waterman, 1978). Practical solutions were scarce, however; because of time-demanding computations, it was not possible to solve problems other than very simple ones. In 1980 the arrival of personal computers and the invention of discretized state Bayesian networks (Pearl, 1985) and efficient propagation algorithm to solve them (Pearl, 1986; Shafer et al., 1987; Lauritzen & Spiegelhalter, 1988; Pearl, 1988) made it suddenly possible for everyone to use Bayes to solve complex real-life problems. The concept of influence diagrams made the theory even more suitable for decision analysis (Smith, 1988; Smith, 1989; Jensen et al., 1990). Soon after appeared the first user-friendly computer software implementation of influence diagrams, Hugin (Andersen et al., 1989). Around the same time, in the late 1980s, Gelfand and Smith (1990) had the idea to combine Markov chains (Metropolis & Ulam, 1949) with a Gibbs sampler (Geman & Geman, 1984) to simulate a joint posterior distribution of the Bayesian model, and the result was Markov Chain Monte Carlo (MCMC). This computationally highly demanding method became feasible with the development of computing power. BUGS (Bayesian inference Using Gibbs Sampling), the first software which utilized the method with Bayesian networks, became a total success (Lauritzen & Spiegelhalter, 1988; Thomas et al., 1992). Both of these innovations together, discretized Bayesian networks and MCMC simulation, paved the way for environmental scientists who were keen to use these new tools to solve many complex problems of natural resource management using decision analysis.

In fisheries management science, the potential of Bayesian methods were already considered in the 1970s (Walters & Hilborn, 1976). The first applications emerged even before feasible tools became available (Ludwig & Walters, 1981; Mangel & Clark, 1983; Hilborn, 1985). The first simple decision-oriented management models appeared around the same time (Mendelssohn, 1980; Fried & Hilborn, 1988). Already in 1988, the first applications of influence diagrams for environmental management appeared (Varis & Kettunen, 1988). The number of applications started an exponential increase after the introduction of MCMC. Unlike in environmental management, in the fisheries field many users adopted MCMC simulation techniques (Hilborn & Walters, 1992), not graphical discrete state Bayesian networks, although there are some exceptions (e.g., Varis et al., 1990; Kuikka et al., 1999; Hammond, 2004; Uusitalo et al., 2005; Uusitalo et al., 2012). Typically, the first influence diagrams were used to describe and solve quite complex problems like the effects of climate change and lake environment management (Kuikka, 1998; Varis & Kuikka, 1999). The details of background processes were not important; they used discretized variables and relied heavily on expert judgment, whereas there was a thorough and very technical guide on Bayesian decision analysis in fisheries stock assessment already over 15 years ago (Punt & Hilborn, 1997). That guide concentrated in stock assessment only and in the meeting of management reference points, going into the details and using MCMC. Since then, a broader view of the problem has been adopted and terms like “holistic” (e.g., Espinoza-Tenorio et al., 2013), “ecosystem approach” (e.g., Garcia, 2003), “biologically realistic” (e.g., Kuparinen et al., 2012), “multi-objective” (e.g., Kim et al., 2003), “interdisciplinary” (e.g., Haapasaari, 2012), and “ecosystem services” (e.g., Landuyt et al., 2013) have become common words in the field. The advantages of the Bayesian approach are noticed increasingly among ecologists (Ellison, 1996; Clark, 2005; Aguilera et al., 2011) and environmental scientists (Chen & Pollino, 2012) though its full potential still remains unexploited (Aguilera et al., 2011). In environmental management, the spatial aspect has been recognized and utilized longer (e.g., Bannerjee et al., 2003; Latimer et al., 2006) but it is an increasing trend in fisheries management, too (e.g., Wyatt, 2003; Ciannelli et al., 2008). Recent developments in methods and computational power have also made them feasible in larger-scale applications (Gelfand, 2012; Vanhatalo et al., 2012a). The view is getting broader all the time; whereas 15 years ago the stock assessment was considered the unit of decision analysis, now we should analyze in the same framework the objectives of all stakeholders and responses from every part of the ecosystem (Varkey et al., 2013). The problem is complex and there are a lot of details that could and should be modeled better and be included in decision analyses of environmental management.

What makes the Bayesian approach especially suitable for the management of environment and its resources? Bayesian inference is based on inverse probability. It means that we observe something and want to know what the probability of the cause is. This makes the method suitable for modeling natural phenomena where we have only the observations but the effects of causes are unclear. Managing environmental resources involves many uncertain factors. If the goal is in extensive high-quality decision analysis, these uncertain details must be included in the model. To quantify these uncertainties, we often need subjective probabilities and expertise from many different fields such as biology, chemistry, environmental sciences, politics, law, human geography and economics (Adger et al., 2003). Combining different types of knowledge is where Bayesian models are at their best (Harwood & Stokes, 2003). Bayesian inference is perfect for decision analysis in cases which are complex and involve many uncertain factors, and where a multidisciplinary approach is needed. Problems are so complex that all causes and effects cannot be understood without organized analysis. To sum it up, a typical decision problem in the environmental field: involves a complex system with uncertain factors which need to be correctly quantified in one framework; involves many stakeholders; is multi-objective; has many decision alternatives; and delivers results that need to be communicated understandably to decision makers and other stakeholders. This is a perfect challenge to be tackled by Bayesian inference.

2 Aims of the study

The problems of environmental management are complex and involve not only countless uncertainties about the nature but also uncertainties in the implementation of management actions. The normal hit phrases of Bayesian inference are that it allows an easy way to combine different kinds of information, learn from previous experiences, and take uncertainty into account in decisions and utilities. In reality, it is not so easy and straightforward to combine all that in one framework and find credible prior distributions, at least if we want to do it properly using Bayesian inference from the beginning and include most of the uncertainties. Of course, there is a common shortcut to use expert knowledge in hard parts of the analysis and thus avoid the modeling of true causalities and fine details behind the uncertain variables. The main contribution of this thesis is in developing methods for modeling those fine details of the system (articles **II**–**IV**). Decision making can be improved by bringing more detailed knowledge of the system and its uncertainties. The aim is in providing better estimates for important variables with realistic uncertainty to be used in decision making. Additionally, in decision making we must have utilities, and some of them are likely based on the value of environment itself—it has no market value. There are not too many efforts to model the uncertainty of this most basic component of decision analysis using Bayesian inference. Paper **IV** tries to answer that problem. At the same time, when fine-tuning those details, someone must make the decisions. Therefore, papers **I** and **V** are more oriented toward applied research and scientific advice.

The specific aims of each research article in this thesis were:

I) To construct a Bayesian network to support decision making in oil spill management at the Gulf of Finland. The specific aim was to assess environmental damages in case of oil spills, and use scenarios to find optimal decisions.

II) To model uncertainties related to acoustic surveys complemented with trawl surveys. The goal was to predict the abundance of three pelagic species using environmental explanatory variables and random spatial effects.

III) To estimate the stock size of two commercially important species in the Greek archipelago. Total catch data was the only available information about these species. We needed to construct a biologically realistic age structured model based on prior information gathered from other areas and similar species.

IV) To analyze data from a single binary choice contingent valuation method to produce an aggregated willingness-to-pay (WTP) estimate for reduction of possible future oil spill damages at the Gulf of Finland. Using the Bayesian approach we wanted to model the uncertainties in the estimate.

V) To conduct the value of information analysis (VoI) to see if perfect knowledge on recruitment would increase the value of the Mauritanian octopus fishery. Additionally, we compared four different utility functions to see whether the aims of different stakeholders could be combined and what the best compromise for management actions would be.

To better understand the problems of decision making and how the research articles are related to it, the following chapters will present the Bayesian decision analysis process in short.

3 Bayesian networks and decision analysis

Bayesian decision analysis is normally coined with Bayesian networks and influence diagrams. In many cases, simple things are hidden behind fuzzy terminology. There is an abundance of different names that are used in relation to Bayesian networks: Bayes networks, (Bayesian) belief networks, hybrid Bayesian networks, object-oriented Bayesian networks, influence diagrams, dynamic Bayesian networks, and the list continues. Some of them are synonyms and some add a minor feature to basic theory. In context of this summary, I have used only the term "Bayesian network" and when I have wanted to emphasize that there are decision and/or utility variables present, I have used the term "influence diagram."

Bayesian networks consist of stochastic variables and arcs connecting them and indicating the direction of the causality. The network must be specified as a directed acyclic graph (DAG). Bayesian rule is used to update probabilities when information is inputted into the network (i.e., we have an observation on the variable). The difference between Bayesian networks and influence diagrams is that in the latter it is possible to add deterministic decision and utility variables that are illustrated differently than stochastic variables, thus allowing complete decision analysis (Figure 1). However, it is not in the scope of this thesis to go into details of calculation and theory behind Bayesian networks. The literature is abundant (e.g., Pearl, 1988; Jensen & Nielsen, 2007; Pearl, 2009; Smith, 2010; Fenton & Neil, 2012).

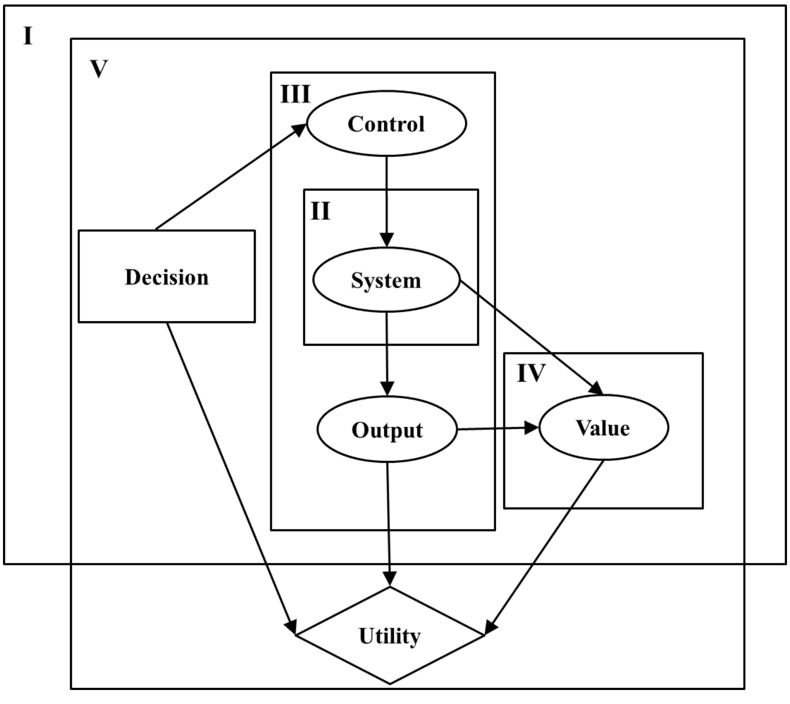

Figure 1. *An influence diagram with all the basic components with their common shapes. The network illustrates a typical decision scenario in environmental resource management, where we have a system which has an output (a resource) we are interested in. Both the output and system have some utility, and especially the value of the system is uncertain. The system can be controlled with decisions in which implementation (control) is uncertain. The decision can come with a cost, which negatively affects the utility. The boxes with roman numerals around different parts of the network show the parts of decision analysis to which each of the articles of this thesis contributes.*

3.1 Tools

The problem with Bayesian networks is that in complex models using continuous variables the calculation of posterior distributions using Bayes' rule becomes hard because there are no analytical solutions. We need methods to approximate posteriors. There are practically two alternatives, discretizing the distributions or numerical approximation of the posteriors. It is possible to implement a Bayesian model starting from scratch but it is more convenient to use some of the existing tools. In this chapter, I will represent the tools I have used in this thesis. The aim is not to provide an exhaustive review of all available tools, but a quick overview of what I have used and how.

3.1.1 Graphical modeling

After the implementation of efficient propagation algorithms for calculating discrete state Bayesian networks, there came a large variety of different software tools. The first ones were simple spreadsheet solutions but soon a variety of tools with graphical user interfaces emerged. Nowadays, there are both commercial (e.g., Hugin[1], AgenaRisk[2], Lumina Analytica[3], BayesiaLab[4]) and open source alternatives (e.g., Genie[5]). There are also freeware versions of commercial tools with limited functionality. A good review of the eleven earlier tools was done by Varis (1997) and another ten years later by Uusitalo (2007), although new tools with improved features are emerging continuously.

The propagation algorithm gives exact answers only with variables with discrete states. Each variable (node) has a conditional probability table, which defines the probability of each state of the variable given its parent node(s). With continuous variables, we must use discretized variables with classified states. Most graphical Bayesian network tools work only with stochastic discrete state variables, but some tools allow the use of deterministic variables and continuous variables. There is at least one tool (AgenaRisk) that allows specifying continuous distributions and discretizes them dynamically. Posteriors are discretized similarly to maximize information content. Another tool (Lumina Analytica) uses MCMC to simulate the posteriors of continuous variables. In conclusion, nowadays there are plenty of different graphical, easy-to-use Bayesian network tools from which to choose. They are the best tools starting experimentation with Bayesian decision analysis. In addition, they are useful in defining the problem field and later in the final decision making for collecting all the pieces of the problem and communicating the results.

We used Hugin in the implementation of the Bayesian network in paper **I**. In paper **V**, Hugin was used to construct a discretized state Bayesian network and to learn the conditional probabilities from the outputs of a simulation model. Hugin was also used to

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[1] *http://www.hugin.com*

[2] *http://www.agenarisk.com*

[3] *http://www.lumina.com*

[4] *http://www.bayesia.com*

[5] *http://genie.sis.pitt.edu*

find the maximum utility policies. With the present version (Hugin Researcher 7.6) it was not possible to calculate VoI with multiple decision variables so that was done by hand.

3.1.2 Numerical estimation

In many models, tools based on the propagation algorithm with discrete states are insufficient. With the discretization of variables, we lose information and conditional probability tables can become very large. Also with very large networks having temporal or spatial dimensions, many graphical tools are probably not the best alternatives. The number of variables can grow very large, although recent developments in the features of graphical software tools that allow object-oriented designs and dynamic discretization have made them more feasible. However, if we want to use continuous variables and the posteriors cannot be solved analytically, instead of the discretization of variables we can simulate the joint posterior using MCMC (Gilks et al., 1995; Gelman et al., 2003).

It is possible to implement necessary algorithms for MCMC in any programming language (e.g., Hilborn & Mangel, 1997). Fortunately, there are tools for that, so there is no need to go into the very details of the mathematics behind the Bayesian inference. Nowadays, many common statistical analysis tools like SAS[6] and R[7] have procedures and packages for MCMC and they can be used very easily without any deeper knowledge of the subject. However, maybe the most popular and oldest tool is BUGS. The success of BUGS is likely in that models can be specified both by drawing directed graphs and by a dialect of S language (Lunn et al., 2012). WinBUGS started in 1989 (the last version was in 2007) but further development is now focused on the open source version of the software OpenBUGS[8] (Thomas et al., 2006). Functionalities and appearance are more or less the same. However, as WinBUGS is no longer updated, it is wise to use OpenBUGS. Although software has a graphical user interface (GUI) and quite a sophisticated environment for analysis and plotting, it is possible and quite common to use it from R. Many statisticians prefer this as they are accustomed to using R, and it offers a better environment for data management, analysis, and plotting (Kruschke, 2010).

JAGS[9] (Just Another Gibbs Sampler) is another implementation of MCMC to model Bayesian networks (Plummer, 2003). It has no graphical user interface but it uses a similar S dialect to BUGS. However, BUGS models do not directly work in JAGS and some manual adjustments are normally needed. JAGS is platform independent where OpenBUGS is not. It is programmed with C++ and Java compared with the outdated Object Pascal used in BUGS. That makes it easier for users to write their own extensions. Also, JAGS supports a 64-bit platform.

Nowadays, there is an abundance of different sampling algorithms other than the original Gibbs sampler. For example, Hybrid Monte Carlo (HMC) (Duane et al., 1987)

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[6] *http://www.sas.com*

[7] *http://www.r-project.org*

[8] *http://www.openbugs.info*

[9] *http://mcmc-jags.sourceforge.net*

was used in paper **II** to simulate parameters that could not be solved analytically. Both OpenBUGS and JAGS implement many different algorithms and automatically assign the most suitable for each variable.

A common term coined with models solved using MCMC is "hierarchical Bayesian model." For some reason, it is not so widely used with graphical Bayesian network models. Actually almost all but the simplest Bayesian networks are hierarchical in a sense, so I do not see the point in emphasizing it. To my mind, a hierarchical model has different levels of hierarchies, where the first level is occupied by variables we are interested in (outcomes), then on the next level comes variables explaining these, on the third level variables explaining variables on the second level, and so on (Figure 2). The priors of the second- and higher-order variables are sometimes called hyperpriors, when on the first level of hierarchy they are referred to simply as priors. However, to my knowledge there is no standardized nomenclature and we must just live with very a diverse and sometimes erroneous use of terms. For another definition of hierarchical Bayesian model in ecological context see Clark (2005).

Initially, all the models in papers **II**—**IV** were implemented with OpenBugs, but in the end, we ended up using JAGS in papers **III** and **IV** and the GPstuff package (see the next chapter) in paper **II**. OpenBUGS has more features, is better documented, and more user friendly, but it seems that especially in many stock assessment exercises, which include long repeated deterministic calculations, JAGS is superior in speed.

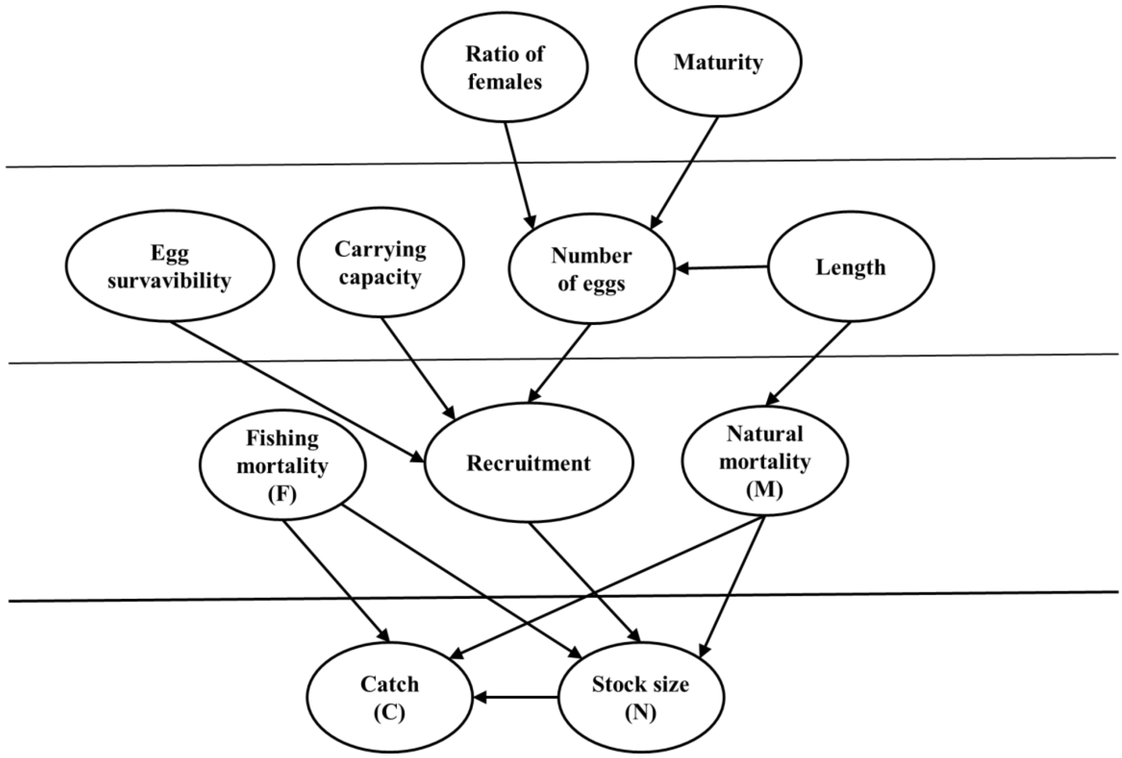

Figure 2. *A Bayesian network describing a model similar to that used in paper **III**. Unlike in the paper, the variables are arranged into hierarchies to clarify the concept of a hierarchical model. The outcome variables are on the lowest level.*

3.1.3 Gaussian processes

The problem of numerical estimation is that it is computationally demanding and solving complex models can take a considerable amount of time. That is why there is a continuous search for more efficient methods for solving complex Bayesian models with continuous variables. One of these methods is the Gaussian process. It can be used to define prior distributions for unknown functions in Bayesian models (Rasmussen & Williams, 2006). In addition to its speed, it is useful in nonparametric modeling and there are many possible uses for it in the environmental field. In fisheries science there are already several applications. For example, Sigourney et al. (2012) model the temporal variability of growth function with the Gaussian process and Munch et al. (2005) use it in stock-recruitment analysis. The Gaussian process is especially suitable for spatial applications. There are examples from the spatiotemporal modeling of discards (Viana et al., 2012), the spatial prediction of bycatches (Aldrin et al., 2012), and distribution of stock or reproduction areas (Gutiérrez et al., 2011; Vanhatalo et al., 2012b).

In paper **II**, we first fitted the spatial models (abundance, length, species composition) using the conditional autoregressive (CAR) method for spatial random effects and Bayesian kriging (i.e., spatial prediction) to predict over all grid cells. With this approach, to keep computation time reasonable, our grid had 203 cells with 20 x 20 km spatial resolution. For better spatial resolution, the same models were consequently fitted using Gaussian process with the GPStuff toolbox (Vanhatalo et al., 2012a) in MatLab[10] for both spatial random effects and prediction. With this approach, we could use 8515 cells with 2 x 2 km resolution. Gaussian process models have become very fast due to algorithmic advances (Vanhatalo, 2010); a great example is where a seemingly overdemanding computation task was resolved when researchers from different fields cooperated.

The problem of Gaussian process is that at the moment there are not yet any user-friendly software applications which would allow their usage by environmental scientists without a considerable mathematical background. Algorithms and calculations must be implemented by the researchers themselves. Another alternative is to use some package (e.g., GPStuff). As in all software, which is not properly tested and widely used, there is considerable probability for the presence of bugs, which may go unnoticed and lead to incorrect results.

[10] *http://www.mathworks.com*

4 Bayesian decision analysis process

There are a great variety of different descriptions for a Bayesian decision analysis process. Most of them are tailored to some specific field or problem. For example, see Punt and Hilborn (1997), Peterman and Anderson (1999) and McAllister et al. (1999) for fisheries management and Eleye-Datubo et al. (2006) for oil spill management. However, essentially all of them contain the same steps. Here, I divide a Bayesian decision analysis process into the following four steps (Figure 3):

1. building a model
2. data gathering and processing
3. using the model
4. post analysis

One important difference from conventional decision analysis is that here I have the building of the model before data gathering. In Bayesian inference, the variables, their causal dependencies, and priors are determined before looking at the data. The complexity of the problem is not dependent on available data and if the data is scarce, then we must rely more on priors. Additionally, I consider it reasonable to combine testing and usage of the model in a single step (3.), as especially in graphical Bayesian software tools, these tasks are done more or less simultaneously.

Simplification of the problem is always necessary in any realistic environmental decision analysis. The boundaries of analysis are defined when building the model. Gathering data involves the collection and elicitation of prior information and the actual data used to update the model. It is important to notice that a Bayesian model can be used without any data (simulated or real). Without data it is still possible to use different scenarios and observe joint distributions of priors without updating. Using the model involves finding answers to the questions set in the first step and confirming that the model works coherently. Post analysis involves communicating results and finding future uses and parts that need improvement. These four steps are discussed in more detail in the following chapters.

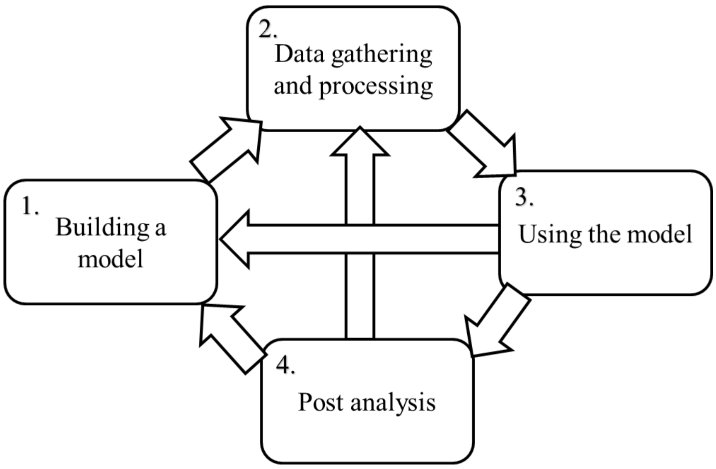

Figure 3. *An illustration showing different steps and their connections in the decision analysis process. It is important to note that if there are problems or a need for improvement in steps 3 or 4 we should go back in the process.*

4.1 Building a decision model

No matter what kind of decision analysis we are making and with what tools, it is good to first graphically define the problem. After the problem is defined, we need to select the most suitable tools for analysis.

4.1.1 Defining a decision model

Every decision analysis must begin by defining a decision problem. Especially important is to think about for whom we are doing the analysis. For example, the decision model of fisheries manager and fisherman are probably very different. The differences are seen in decision and utility variables, although otherwise the basic structure could be the same; both models share similar variables describing the status of the stock. However, even the causalities can be different and that is important to consider (Henriksen et al., 2007; Mäntyniemi et al., 2013). It is possible to construct several structurally different models and compare or combine results later on (Maxwell et al., 2006). For decision makers the objectives are normally quite clear, but a researcher seeking to give scientific advice should be aware of what the goals are and within which frames the decision is made. There may be conflict when a researcher, advisory in mind, has constructed a decision model for a situation that is useless in decision making or answers a wrong question (Liu et al., 2008). Of course, this problem arises only in applied research because academic research is free of outside influence.

The definition of a decision model can be divided into four parts. First, we start by finding our objectives—what are the questions we need to answer? For example, what is the maximum sustainable yield of a fish stock? What oil-combating measures are the most efficient and worth investing in? These questions help in finding proper decision and utility variables in part 2. After the objectives and related utilities and decisions are clear, we must define the system and relevant variables in it (part 3). A model is always a compromise and the level of detail is dependent on how much resources can be put into development. However, the most important variables should be identified and included in the model. After all the relevant variables describing the system are collected, the causalities between them are defined (part 4). Using expert knowledge in the description of the system and definition of causalities is recommendable.

1. Define the objective(s) of the analysis.
2. Define decision variables and alternatives.
3. Define relevant variables describing the system.
4. Define causalities between the variables.

In papers **I** and **V** I present decision models (although in paper **I** there are no utility variables) both looking at the problem from a resource manager's point of view. In defining the relevant variables of paper **I**, I consulted the experts of both oil spill management and ecology. The final model structure was approved by the person in administrative charge of coordinating the oil spill recovery efforts of Finland. The decision model in paper **V** combines different objectives of stakeholders and compares their utilities under different management scenarios and environmental hypotheses.

4.1.2 Selecting methodology and tools

It is very important first to define the decision problem and only after that decide what methodologies and tools are used. The complexity of the problem and amount of uncertainty are important things to consider when selecting proper tools. In some cases, a simple deterministic decision tree could do the work most efficiently. It is important to constantly check for new tools and solutions, and not stick to an old and comfortable one. A few days spent learning the secrets of a new tool could save weeks or even months of work; I have personal experience in that matter, when after weeks of fighting with convergence problems and error messages with BUGS, the model in paper **IV** ran immediately without problems in JAGS.

In this thesis, we are interested only in Bayesian methods. Fortunately, it is very well suited to the environmental field, which is full of uncertainties. There are still a variety of tools to choose from and the choice is dependent on the complexity and type of problem. In problems where expert elicitation is needed, graphical Bayesian networks and influence diagrams are more easily communicated to experts. In addition, graphical tools have some inbuilt features that can cut down the amount of manual programming, such as VoI and other sensitivity analyses, finding optimal decisions and maximum utilities. Bayesian networks work well with binary, ordinary, and nominal variables, whereas with continuous variables MCMC is a logical choice. In complex cases it may be useful to divide the problem into submodels and analyze each of them separately using a suitable tool for that particular problem. Tools used in this thesis were presented in the previous section.

4.2 Data gathering and processing

In Bayesian decision analysis it is good to make a distinction between observed data and information and data gathered to form priors. Observed data should not affect our priors and should be looked at only after the priors are formed. Bayes' rule is applied after observed data is inputted into the model. Especially in many risk assessment applications, where we are modeling something that has never happened before or that happens rarely, there is no observed data and the model is built based solely on prior information. Serious efforts should be put toward the gathering of all available data and information for priors. However, it is good to remember that while priors are important, reliable observed data is even more informative. Data gathering and observation programs should not be overlooked. That is the only way to observe changes in the system.

The main contribution of the thesis is in this step of decision analysis. How do we attain more reliable priors for variables in the decision model? Papers **II**–**IV** are dedicated to this theme. Actually, paper **III** goes into very fine details of stock assessment and tries to improve survey results that are used as indices to stock size. However, there may be significant uncertainties involved in these processes and they should transfer to the upper level and finally cumulate into the result of a decision model which is used in decision making or advice. In addition to observed data and prior information, information is needed to form utility functions, which are an essential part of the decision analysis. Paper **IV** is about accounting for uncertainty in environmental valuation, of which results are used as utilities in decision models.

4.2.1 Prior information

In principle, there are two options for prior information: non-informative or informative. Non-informative priors bring only vague information about a variable. The line between informative and non-informative is not always clear and terminology is not fully established. In this thesis the focus is on using the best possible and available information in forming prior distributions and non-informative priors are not discussed deeper (e.g. Berger & Bernardo, 1992). Weakly informative priors (i.e., very wide distributions) are needed, for example, in variance parameters of models (Gelman et al., 2003; Gelman, 2006). Generally, fat-tailed distributions are favored as informative priors, as they are more robust to outliers and misspecification (Chen et al., 2000). According to the views of some, only non-informative priors should be used; in their minds, informative priors are distorted by the subjective beliefs of scientists (Walters & Ludwig, 1994). Thus it is important that elicitation is done carefully, whether distributions are from experts or literature. In the following chapters, I will discuss different methods for forming prior distributions.

4.2.1.1 Expert elicitation

Elicitation of probabilities from experts is not a simple task and requires careful design and expertise. There are many guidelines and protocols for the elicitation of expert knowledge (e.g. Meyer & Booker, 2001; O'Hagan et al., 2006). A good elicitation procedure should not be just a sequential order of steps but should have a feedback cycle where both elicitator and elicitee can adjust the probabilities. It is also recommended to use several experts. After the probabilities are elicited they should be validated somehow. A common procedure is to use scoring to adjust experts' probabilities based on their previous performance and creditability.

Expert elicitation is widely used in environmental decision analysis. Varis and Kuikka (1997) presented a framework, Bene-Eia, for expert elicitation in environmental decision making and León et al. (2003) used a Bayesian framework for elicitation in an application of benefit transfer of environmental goods. In fisheries management, which is more data-oriented, there are not so many research papers utilizing expert knowledge. In analyses which incorporate a lot of biological details or in integrative models, it is used to formulate informative priors to substitute otherwise heavy data gathering (Uusitalo et al., 2005; McAllister et al., 2010; Haapasaari et al., 2010; Mäntyniemi et al., 2013).

However useful and convenient the expert elicitation is, at the same time it is infested with pitfalls and problems (Wolfson et al., 1996). Problems were recognized already decades ago and there is abundant literature about them (Tversky & Kahneman, 1974; Kahneman et al., 1982; Kynn, 2008). Researchers eliciting expert knowledge must be aware of these problems and somehow address them, otherwise the results may be seriously biased (Clemen, 2008). In environmental decision analysis, there are no standard commonly accepted procedures for elicitation. Experts of behavioral sciences should be consulted and involved in elicitation to guarantee that it is done properly (Clemen, 2008; Flander et al., 2012). One frequent problem in elicitation is to familiarize the expert with the Bayesian technique and priors. Additionally, many experts are very busy and cannot dedicate too much of their time, and can reside on the other side of the globe. One solution is to use web-based tools, which offer easy and fast ways for the gathering of expert knowledge (Bastin et al., 2011; Truong et al., 2013). Although there are many problems and pitfalls in elicitation, at the same time it is that where the power Bayesian inference comes: ability to incorporate subjective expert probabilities in models and thus produce more realistic results to decision analysis.

I have used expert knowledge when formulating priors in paper **I**. The environmental effects are based on that work. There was one expert who had several months to do the work. The basic idea of discrete Bayesian networks was introduced to the expert and she was given the probability tables (quite large and numerous), which she filled in based on her expert opinion and exhaustive literature review. Nowadays the tools are improved and the same job could be done faster, for example by eliciting continuous distributions, and discretizing them later on (or using continuous distributions). Thus it becomes unnecessary to fill in thousands of separate conditional probabilities.

4.2.1.2 Literature and previous studies

The Bayesian inference is based on learning from previous experience and updating it with new observations. Using previous studies and existing knowledge in forming priors should be self-evident. In fisheries science meta-analytic approaches are well known and there are many efforts to further usage of existing knowledge (Hilborn & Liermann, 1998; Myers, 2001; Millar, 2002). Primarily, information from the same population should be used, but in its absence, it is still possible to use information from other areas and related species. To maximize the use of existing information, the posteriors of every Bayesian study should be reported in some standardized, easy-to-use format to be used as priors in forthcoming studies. One possible location to store that data is Fishbase. It is a project which aims to collect basic biological data on all fish species of the world (Pauly & Froese, 1991; McCall & May, 1995; Pauly, 1997; Froese & Pauly, 2013). However, there are problems in its data quality and researchers should pay extra attention when retrieving information from it (Courtney et al., 2011).

In paper **I**, the environmental impact part was based on a meta-analytic approach combined with expert knowledge. Also, many other priors (e.g., spill size, weather conditions, oiled coastline) were formed using existing literature. The model in paper **III** was an exemplary case, where priors of biologically realistic age-structured stock assessment models were gathered using only information from other areas and species. Finding relevant priors for every variable was a considerable job. It was quite easy to find mean or median values for priors, but finding justified distributions for them was a challenge.

4.2.1.3 Submodels

A decision model should be easy to understand and at the same time as complete as possible. Therefore it may be useful to include only the most important variables in the final decision model, which is used to find maximum utility policies and in communication of results. Details can be hidden in submodels or modeled with other tools. Influence diagrams are suitable for the presentation and analysis of a final model, whereas many subproblems are maybe easier to implement using other tools. In complex problems which combine knowledge from many different disciplines, it is only natural that submodels are separately implemented by dedicated teams of experts. Of course, the integration of a final model and coordination of the development of submodels are considerable tasks. Even combining all the details of a stock assessment model is not straightforward (Michielsens et al., 2008).

Papers **II**, **III** and **IV** are examples of submodels dedicated to solve one or a few specific variables to be used in an actual decision model. Two of them contribute to a more accurate estimation of stock size. The results of paper **IV** were later used in a decision model, which was a cost-benefit model to find cost-efficient methods for the mitigation of oil spill-related damages to the environment.

4.2.2 Utility functions

Utility functions, measures of value, are needed in decision analysis. Without them it is impossible to find maximum utility, which is part of the definition of decision analysis. The objectives and thus utility functions of different stakeholders might be very different (Borsuk et al., 2001). The utility is always dependent on a decision maker and in many cases it is not the scientists' job to assign them, but the decision maker decides the importance and value of different variables and assigns utilities accordingly. Paper **IV** is an important improvement toward better utility functions, where the utility itself is uncertain. In paper **V**, we use multiple utility functions to describe the goals of different stakeholders. In applied research and scientific advice it is normal to use money as a measure of utility, because the users of information are managers and politicians, who understand things best when measured in money. Therefore, the next chapter is about environmental valuation.

4.2.2.1 Environmental valuation

When a variable of interest does not have a clear monetary value or its utility is non-market, we need valuation to convert it to the same units with other utilities, which are normally monetary. Especially in environmental decision analyses, where we have to consider the utilities of all stakeholders, we need tools for valuing environment. Contingent valuation is maybe the most used method in the field (Hanemann, 1994; Bateman & Willis, 2001) and there is a widely accepted guideline on how to use it (Arrow et al., 1993). The results of contingent valuation studies can be used directly in decision making, as in the case of the Exxon Valdez oil spill (Carson, 1992; Carson et al., 2003). This incident made the method popular and it was used later in similar cases when valuing environmental losses after an oil spill (Biervliet et al., 2005; Loureiro et al., 2009). In fisheries science, it is used especially in the valuation of recreational fisheries (Daubert & Young, 1981; Hoehn, 1987; Carson et al., 1990; Layman et al., 1996; Roth et al., 2001; Parkkila, 2005).

There has been a lot of critique and controversy around contingent valuation (Diamond & Hausman, 1994; Hausman, 2012). Nevertheless, it is increasingly used in many applications, mostly because there are no better alternatives. As the trend is now moving toward an ecosystem approach in the use of environmental resources, it may become frequently necessary to valuate non-market utilities of the ecosystem and these values should be part of the complete decision analysis. Paper **IV** presents an approach where uncertainties of contingent valuation are clearly formalized and modeled in one framework. The goal was to have the uncertainty of final value presented in one distribution, which is causally and logically justifiable and thus useful for decision makers.

4.3 Using the model

Once the model is ready, it is time to experiment with it and test that it produces logically correct results. In a decision model, the goal is in finding the optimal decision or combination of decisions yielding maximum utility. After performing the actual analysis, the model should be tested somehow to be sure that results are coherent and stable. Sensitivity analysis is maybe the most common way to test a Bayesian decision model. Value of information is one type of sensitivity analysis and is discussed later on. If serious defects are detected, then it may be necessary to go back to step 1 or 2 of the decision analysis.

4.3.1 Obtaining results

The result of a decision model is the decision yielding maximum expected utility. Finding it is straightforward and automated in many software tools. In research-oriented decision models it is typical to play different scenarios and observe outcomes. In fisheries management science it is common to find an optimal decision (e.g., level of fishing mortality) that corresponds to the maximum sustainable yield (MSY) or some other reference point. There are a set of common reference points (Caddy & Mahon, 1995) that are typically used on management of fish stocks.

In paper **I**, we used different oil spill accident scenarios to compare and predict possible effects on the ecosystem both immediately and ten years after the accident. It is common to include the "worst case scenario," which tries to mimic the worst possible outcome. With the decision model of paper **V** we found optimal decisions in four different scenarios and used the value of information analysis to find the expected utility if we had perfect information on recruitment.

4.3.2 Model testing and sensitivity analysis

With more data-oriented applications and models used in decision support and advice, it is typical to test different model structures using different combinations and effects of explanatory variables. Model validation with data not used in model construction is normal to test the prediction capabilities of the model. In influence diagrams prior sensitivity analysis is used to find variables having the largest effect on the utility. For details in model testing and sensitivity analysis readers should refer to abundant literature (Pratt et al., 1995; Smith, 2010; Fenton & Neil, 2012; Marcot, 2012).

The models in papers **I** and **V** are closest to complete decision models, which can be used to support decision making. However, in paper **I,** there are no utilities and in paper **V**, the model is designed to be used for VoI analysis, and we do not do any other model testing. However, the next chapter is dedicated to VoI, which is one type of sensitivity analysis.

4.3.3 Value of information

In a complete decision analysis model, with decision variables and utilities, we could perform VoI analyses. VoI tells how much at most a decision maker should pay to resolve some uncertainty. The full theory behind VoI is explained by Smith (2010). In environmental research literature, VoI analyses are rare. In the context of fisheries management there are some examples (Varis & Kuikka, 1990; Varis et al., 1990; McDonald & Smith, 1997; Link & Peterman, 1998; Kuikka et al., 1999; Punt & Smith, 1999; Kim et al., 2003). The concept of VoI in fisheries management is described by Kuikka (1998) and later with a good step-by-step guide on how to use it by Mäntyniemi et al. (2009). In paper **V**, we make a more complex VoI analysis to show its potential in fisheries management. Researchers of environmental economics are too interested in VoI analyses (Moxnes, 2003; Forsberg & Guttormsen, 2006; Hansen & Jones, 2008). Yet again, a place where cooperation between different fields of scientists should be used to produce realistic and high-quality VoI analyses into decision models. Economics could provide the utilities and cost functions whereas biologists should produce the realistic description of biological systems. If one or the other part is poor, the results will also be.

In addition to the value of information, the Value of Control (VoC) is a useful decision analytic tool. It tells expected utility gained from having perfect (or better) control over uncertain variables. Using both VoI and VoC, we could determine where resources are used most efficiently, in data gathering or improving control. An example of VoC analysis in lake management is given by Varis et al. (1990) and in fisheries management by Link and Peterman (1998).

4.4 Post analysis

Post analysis is an important step in every decision problem. After the results are ready and found to be consistent they need to be clearly communicated. Things needing improvement and problematic parts need to be honestly reported to be improved in further analyses.

4.4.1 Communicating results

Scientific advice is very different from actual decision making, where a decision maker must make a decision based on the best available information. This is a very important difference. Where decision makers are often held responsible for their decisions, scientists are seldom held responsible for their advice. However, there is a recent case, where Italian scientists were convicted of manslaughter due to their “false” advice concerning the probability of an earthquake which eventually happened and killed over 300 people (Nosengo, 2012). The story is a tragic reminder that scientists must be careful when giving advice and especially how they give it. Proper communication of uncertainty and probability plays a very important part in scientific advice.

Bayesian decision models are fortunately very useful in the communication of results. When presented in graphical format, it is clearly visible where uncertainty cumulates and what the assumptions are behind the model. The model is not just a black box where something goes in and something comes out and where the uncertainty is dug out of fractions of variance, which itself is derived so complicatedly that the decision maker could not ever grasp the idea behind it. Understanding the reasoning behind a decision model should improve the quality of decisions and provide some comfort to the decision maker. Communication is its own field of study, and yet another place where the skills of experts from other fields should be used. A review by Spiegelhalter et al. (2011) is a good starting point to the visualization and communication of uncertainty.

4.4.2 Reuse of the model

The idea is that every decision model should be documented so that it can be reused; it is absolute ludicrous to reinvent the wheel again and again. At the same time, it is good to collect ideas on how to improve the model in further analyses and report flaws honestly.

For example, in fisheries management many stocks are assessed yearly. There is a good possibility to improve the model iteratively and every time to reflect how the last version succeeded in predicting the stock size of the present year. However, if there is clear evidence that better alternatives are available and management results have been poor, there needs to be courage to discard the present model and start with a new one.

Paper **I** is an example of a decision model that is improved step by step in further studies. In all papers, I have reported the parts that are most problematic and need improvements. Additionally, every stochastic variable is updated in the Bayesian model and these posteriors can be used as priors in future analyses by other researchers. Therefore, it is important to make posteriors available. For example, in paper **III**, we reported posteriors for key population parameters, so that they can be used as priors in further analyses. In general, it would be good if researchers would submit more of their models and codes as the electronic appendices of journals. I am ashamed to admit that this is something I have not done.

5 Results and contribution

I have contributed to all four steps of the decision analysis process. Paper **I** is where every decision analysis starts (step 1), a simple presentation of the problem at hand where the most important variables and their causalities are defined. This elementary model can be used to find the subjects that need more study. Papers **II**, **III** and **IV** are examples of how Bayesian methods can be used to produce more accurate information to decision makers to be used in their decision analysis (step 2). Paper **V** is about using the decision model to estimate VoI and finding decision policies yielding maximum utilities (step 3). Finally, paper **I** is an example of how the model is reused and improved, in part by others and in part by me (step 4). I am not going to replicate the results of each research article in more than a few sentences but will describe their most important contributions and how the research relates to the bigger picture in decision analysis.

In paper **I,** the aim was to make a simple decision analysis framework for analyzing the environmental effects of an oil spill. The model was based on prior information and done with Hugin. It allowed for testing of different accident and mitigation scenarios and their effects on the environment. The original model was not peer-reviewed but was later published as part of a more complete model (Lecklin et al., 2011), which improved the environmental impact part of the model. The model is very simple, priors are not very well justified, and expert elicitation is implemented inadequately. However, this was a very significant first step in a series of research projects, which incrementally improved this basic framework, and that is why I included it in this thesis. This case is an excellent example of how the fourth step in the decision analysis process is properly utilized and shows how every decision analysis starts from a simple outline of the problem. This first model revealed the most problematic parts that needed more research. One problem was the recovery efficiency, which is now modeled in detail by Lehikoinen et al. (2013). Yet another problem was that it was hard to model the whole Gulf of Finland at one time and Helle et al. (2011) made a more specific assessment in one area. This first decision model also revealed that for a more complete analysis it is very important to involve scientists from different fields to get better results (Klemola et al., 2009). Now engineers are involved in the modeling of accident probability and outflow scenarios (Hänninen et al., 2012; Sormunen et al., 2013). One shortcoming of this simple model was that there were no utilities. The first step to correct this flaw was a conventional valuation study to get an approximate value for the oil-free nature of the Gulf of Finland (Ahtiainen, 2007). Later we wanted to have an estimate for uncertainty in that WTP estimate and it was then implemented in paper **IV**. At some point, these improvements should be again integrated into one decision model, which would provide an updated and more accurate view of the problem.

In any stock assessment model the stock size is the single most important variable (Hoggarth et al., 2006). In fisheries decision analysis, a good estimate of stock size is maybe the most important variable. Typically, it is linked to all outcome variables that interest us in decision analysis. So it is very important to develop methods that could lead to more accurate estimates and with realistic levels of uncertainty. The method presented in paper **II** is one step toward more accurate stock estimates and thus contributes to more realistic results in decision analysis and most importantly accounts for the uncertainty in the estimate. To get biomass estimates for the three most common pelagic fish, we combined three spatial model layers, abundance, length, and relative proportion of species. The model showed that predicting the results of acoustic surveys over a large spatial grid leads to significant uncertainty in the results. That is why acoustic surveys are normally used only as relative indices in stock assessment to tune stock estimates (Simmonds, 2003). Additionally, in the paper we used spatial Bayesian methods, which allow fast inference and thus applications with better spatial accuracy and coverage.

Paper **III** presents a case study where the stock sizes of two poorly studied species were modeled and contributes to the same theme as paper **II**. The main result of the paper is the stock estimates for these two Mediterranean species using a biologically realistic Bayesian model, where prior information was collected from other areas and species. A variety of different methods were used in formulating prior distributions. Both species are hermaphroditic, which adds its own problems in the age-structured model. Essentially the model accounts for biological uncertainty (Kuparinen et al., 2012) that would be otherwise dismissed in simpler model structures used to analyze data-poor fisheries. Sometimes simpler is more effective and produces results but at the same time omits important sources of uncertainty. The decision makers get a more realistic picture of the status of stock and most importantly the uncertainty in that estimate. However, in this case the model was deemed to be insufficient for use in decision analysis. Another implication was that a more comprehensive data gathering program should be established and the behavior of fish in the area should be studied better. It is important to recognize when the data or model are not sufficient for decision analysis and thus knowingly provide overly specific false advice for management.

Paper **IV** is an important step toward a more comprehensive Bayesian decision analysis in environmental sciences where some of the utilities reflect non-market value. We presented in the paper a Bayesian method for analyzing the results of commonly applied valuation methodology, contingent valuation. Using a Bayesian model, we accounted for the most important sources of uncertainties in the result. The approach is unique in that it includes uncertainties from all levels of analysis and presents results straight in a population level, which is important in decision analysis. The paper uses novel methodology in addressing the common nuisance in valuation studies: non-response. Bayesian analysis is not commonly applied in this field of economics and in that way, the contributions of this paper are significant. The developed method was used in analysis of contingent valuation data on willingness to pay for improved oil spill preparedness at the Gulf of Finland (Ahtiainen, 2007). One of the results was that non-respondents' WTP may be significantly lower than respondents'. The results of the paper are readily available for decision makers. The final result, WTP in population, was used in a Bayesian cost-benefit analysis, where different oil spill mitigation measures were compared and WTP was used as a measure of benefit from a cleaner environment.

The decision model in paper **V** is the closest one to a complete and usable decision model in this thesis. Its results are straightforward and useful in fisheries management advice. Value of information analysis showed that the knowledge of recruitment is not needed in the successful management of the Mauritanian octopus fishery. Additionally, we presented maximum utility decision policies for 40 different scenarios (10 recruitment hypotheses and four utility functions), and based on these we recommended boundary values for fishing mortality and the minimum landing weight of octopuses. Other than being useful in management, the paper contributes to the increasing common knowledge of VoI analysis and its possibilities. Finally, this paper demonstrates how stock assessment modeling could be further used in more thorough decision analysis.

6 Discussion and conclusions

The contribution of this thesis is mostly in details, which are commonly discarded from a decision model as insignificant. In environmental decision making, we must consider sociocultural, economic, and biophysical aspects (Matthies et al., 2007). Ideally, all these components should be in one modeling framework. It is true that simpler models could be more suitable for management (Butterworth & Punt, 1999; Hilborn, 2003). However, the aim of science is not in simplicity—applied research is different than academic research. It is important to find simpler solutions and provide useful scientific advice. At the same time we must try to achieve a better understanding about the true processes and causalities of the system, which includes not only the ecosystem but also humans. It is hard to combine these two things, giving decision makers what they want, while at the same time producing novel scientific methods (Kraak et al., 2010).

Decision analysis is multidisciplinary by definition and environmental decision analysis is even more so. "Divide and conquer" has long been known as the key to success in decision analysis (Keeney, 1982), but it involves more than dividing problems into subproblems. The experts of different fields should be assigned to each subproblem needing special expertise and someone should put all this information together. Often a decision maker is left alone to put up different pieces of the whole decision problem. In complex cases it is impossible for a decision maker to combine all the information and come up with an optimal decision. A decision maker has to consider economic efficiency, environmental effectiveness, equity, and political legitimacy of the decision (Adger et al., 2003). There is an evident need for decision support tools that could help in putting all the information together.

Bayesian decision analysis is not yet common in the environmental field, nor among researchers, and even less among decision makers (Aguilera et al., 2011). One of the reasons is the availability of suitable tools. A review of Bayesian networks in environmental and resource management (Barton et al., 2012) and many stock assessment models (Hilborn, 2012) show that there is a great diversity of good models available. However, hardly any of them can be considered an off-the-shelf type of environmental decision support system, which could be directly used by a decision maker. There is an apparent need for the productization of dedicated user-friendly Bayesian decision tools for environmental management. Most of the dedicated environmental decision support systems are deterministic (Christensen & Walters, 2004; Smith et al., 2007; Jakeman et al., 2008; Huang et al., 2011). Uncertainty in environmental processes is acknowledged but a common solution is to recommend improved data-gathering programs or uncertainty is accounted for using scenario analyses (Matthies et al., 2007). Another reason is that managers may have problems using complex models and prefer simpler ones they can understand (Hilborn, 2012). One widely used decision tool for aquatic ecosystem management, Ecopath with Ecosim[11] (EwE), has one Bayesian component, but it is rarely used, because it is a very demanding task to describe prior distribution for all input parameters (Christensen & Walters, 2004). I made exactly the same observation when

[11] *http://www.ecopath.org/*

gathering prior information for the model constructed in paper **III**, where the description of the system was still quite simple and the number of priors moderate.

Many graphical Bayesian networks software tools are very capable and user-friendly. However, for managers they are too general and for researchers they offer only limited features and capabilities. Complex model structures with continuous variables need other methods. Software tools for these are not user-friendly. Both JAGS and BUGS need substantial knowledge of Bayesian statistics and familiarity to programming. Also, it remains unclear how well they are tested against errors. Longer history and a larger user group favor BUGS. In addition, it is more user-friendly but common users can easily run into problems with the software or use it in the wrong way. For some reason the authors have not considered it necessary to restrict mathematically or logically incorrect actions (Lunn et al., 2009). A good tool should not only provide correct results but should also prevent users from performing wrong actions. It is not a reasonable assumption that every user of Bayesian methodology is an expert in it. There are no remarkable improvements in sight to present MCMC, and the future methodological developments in Bayesian inference probably come from the field of machine learning (Lunn et al., 2009). In the last 20 years most of the advances in the complexity of Bayesian models are thanks to the increased computation power of desktop PCs more than advances in the methodology. However, new tools such as Gaussian processes can change this, as application of it in paper **II** showed. Not only Gaussian processes but also spatial applications in general are gaining more interest all the time. Integrating discrete Bayesian networks with geographical information systems (GIS) produces interesting results that are easy to visualize and communicate (Burgman et al., 2010; Chen & Pollino, 2012) and are not computationally demanding.

There is still a lot to be done to improve Bayesian decision analysis. Bayesian methods are used increasingly in stock assessment to give scientific advice (Hilborn, 2012; Maunder & Punt, 2013) but the problem is much larger and decision makers cannot make decisions based only on the size of stock. Basic research should concentrate on producing better and more complete models of the whole ecosystem and related stakeholders. There are some examples of decision analytic Bayesian models that try to combine not only biological but also ecological and economic dimensions (Levontin et al., 2011, Varkey et al., 2011) or social dimensions and human behavior (Fulton et al., 2011; Haapasaari, 2012) of fisheries management. At the same time, the goal of scientific decision analysis should be in direct support of management and policy development. The results need to be clearly communicated and visualized. Booshehrian et al. (2012) give an excellent example of how complicated models and uncertainty should be communicated. In addition, a risk analysis framework could be useful in the communication of results. It can be regarded as a special case of decision analysis, where the aim is to model factors affecting the risk event and its outcome (Fenton & Neil, 2012). The goal of risk analysis is to find the best decisions in order to mitigate both probability of a risk event and its negative consequences. For example, the risk event can be the collapse of a fish stock (Collie et al., 2012) or consequences of an oil spill (Carriger & Barron, 2011). The results of risk analysis are maybe more easily communicated to decision makers and make problems more apparent. Policy analysis is another closely related concept to decision analysis, but its scope is in larger-scale policies and their effect on the system (Power & McCarty, 1997).

Although the scope of this thesis is not in full decision analysis, but in improvement of details, there has still been a need for interdisciplinary work. My co-authors have a very diverse background. They include several fish biologists, applied mathematicians, a statistician, an engineer, and an environmental economist. Additionally, an even wider range of scientists was used as the source of expert knowledge and my own background is divided between fisheries and computer science. How is interdisciplinary research accomplished? Interdisciplinarity is most fruitful in situations where experts of different fields work together. They have to understand each other's fields of expertise to some degree, though not thoroughly. If a subproblem is possible to separate and be done by the experts of some field, it should be done. Then all they need to know is how their work relates to a bigger picture and what is needed as output from their work. In making this thesis I have been mostly responsible for both method and subject. I had to learn a lot. It is a privilege but has taken a considerable amount of time. However, in my opinion this is not how interdiscpilinarity should be handled. When making a fisheries decision model, it is not a biologist's work to do economic analyses or go into specific problems of acoustic surveys. For interdisciplinarity to be efficient, a leader of the work should master the subject and consult the necessary experts regarding the method. In many cases, I found myself consulting different experts (of method and subject) and acting as interpreter between them but at the same time not understanding either of them. In the end, I had to master both subject and method to be able to produce any reasonable scientific output. Scientific research is not about being "the jack of all trades" but concentrating in one subject or method and mastering it thoroughly.

In my opinion, decision analysis alone will not solve the problems of environmental management. Especially in fisheries management, where the problem is overfishing and that is because of politics, policies, and poor control. However, a comprehensive decision support system that captures all the essential aspects of the whole decision problem, quantifies uncertainties credibly, and predicts correctly responses from the system, could assure managers, stakeholders, and politicians that fisheries could be managed more optimally. At the moment, we are still far away from that.

In conclusion, the results found in this thesis are small but important steps toward better and more comprehensive Bayesian decision analyses in environmental and fisheries management. I do not try to offer one correct and complete way to make Bayesian decision analysis. I hope that I have opened some eyes to see how complex and full of uncertainties the decision problems are. One important thing in this thesis was the cooperation of scientists from many different disciplines with a variety of backgrounds. Interdisciplinarity is the key to comprehensive and high-quality decision analysis.

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