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Experiences in Bayesian Inference in Baltic Salmon Management

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Abstract. We review a success story regarding Bayesian inference in fisheries management in the Baltic Sea. The management of salmon fisheries is currently based on the results of a complex Bayesian population dynamic model, and managers and stakeholders use the probabilities in their discussions. We also discuss the technical and human challenges in using Bayesian modeling to give practical advice to the public and to government officials and suggest future areas in which it can be applied. In particular, large databases in fisheries science offer flexible ways to use hierarchical models to learn the population dynamics parameters for those by-catch species that do not have similar large stock-specific data sets like those that exist for many target species. This information is required if we are to understand the future ecosystem risks of fisheries.

Key words and phrases: Bayesian inference, Baltic salmon, risk analysis, fishery management, decision analysis.

1. INTRODUCTION

We introduce a case of fisheries management where Bayesian inference has been extensively used. Fisheries management is a field of applied science, and one could easily argue that fisheries science is as close to politics as science can be. Fisheries scientists routinely advise managers and politicians about possible catch allocations for the near future. This advice has to be concentrated on aspects relevant to the objectives defined by legislation and international agreements [8]. Such advice is a highly charged issue, since fishing is probably the best known example of the tragedy of commons (i.e., the depletion of a shared resource by individuals contrary to the group's long-term best interests [6]) brought into public awareness by the collapse of arctic cod stocks in 1992 which rapidly resulted in the loss of over 40,000 jobs in Canada [9]. Even though Bayesian models are becoming increasingly common in fisheries management due to the adoption of the precautionary approach, it remains a challenge for a scientist to tell a fisherman, "You need to cut down your income this year because I am so uncertain about the consequences of your fishing."

Thus, fisheries management is an area of risk analysis where it is crucial for effective decision-making to utilize all potential information sources and to make scientifically sound estimates. Specifically, fish management policymakers need to be given sound estimates of the uncertainties involved in predictions about how stock will develop under each alternative management action that can be made in the near future.

This application requires Bayesian decision analysis [12], by which one can analyze the role of alternative information sources in support of decision-making and the effects of alternative decisions on various aims of stakeholders and society. Moreover, the possibility of using expert knowledge in addition to data [14] is useful when creating complex models for risks which have not yet occurred.

In addition to the obvious scientific reasons for applying Bayesian inference in fish stock assess-

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ment [24], there is also a legislative reason for methodology. Because all fisheries legislation has incorporated a precautionary approach [2], policies should be risk averse and account for uncertainty estimates. By providing scientifically justified statements of uncertainty, Bayesian stock assessment models can help in such a process. In particular, assembling prior probabilities from existing literature, still an underutilized approach, can be useful.

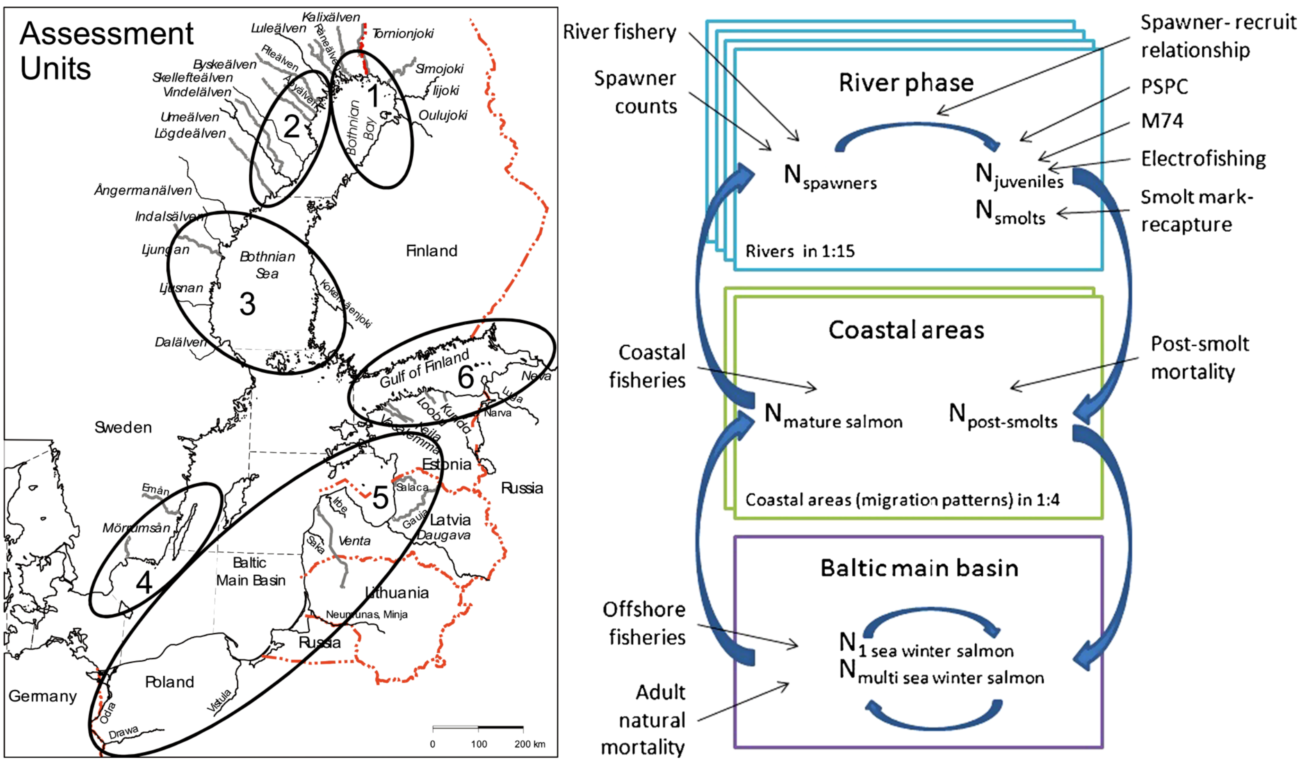
2. BALTIC SALMON FISHERIES MANAGEMENT

2.1 The Baltic Sea

The Baltic Sea is a brackish water ecosystem with several unique features. The salinity varies from around 20 per mille in the south to close to freshwater at the end of the Bothnian Bay and the Gulf of Finland [Figure 1(a)]; as a result, most Baltic sea species are genetically unique. Predicting future changes in the Baltic sea ecosystem is challenging owing to, for example, the unpredictable periods of low oxygen levels. Future salinity and nutrient levels may also be different than those observed in historical data [3]. It is also expected that climate change will further impact both the salinity and the temperature of the sea [7]. For these reasons, historical data alone is not sufficient for predicting the future.

2.2 Baltic Salmon

Baltic salmon are a geographically isolated population of Atlantic salmon (*Salmo salar* L.), which can be further divided into subpopulations, called stocks, corresponding to their spawning rivers. The salmon is a migratory species that spends its first years in a river, travels to the open sea for its feeding migration and returns to the river to spawn [see Figure 1(b)]. Since each salmon subpopulation returns only to its native river to spawn, maintaining all stocks in a healthy condition is an important task for fisheries management. Owing to the high level of exploitation in the early 20th century, the abundance of wild Baltic salmon dropped significantly until the 1980s. In addition, the damming of rivers has reduced or even eliminated the possibility for successful natural reproduction in many Baltic rivers [10, 11, 25]. In order to compensate for the losses of natural reproduction, hydropower companies are obliged to release reared salmon annually into the mouths of dammed rivers. This activity increases the fishing potential but provides yet another challenge for



(a) The spawning rivers and assessment units of Baltic salmon [11]

(b) The life cycle of salmon

FIG. 1. *The Baltic sea and the life cycle of salmon.*

wild salmon management, since the fisheries cannot distinguish between reared and wild salmon. Recruitment of reared stocks cannot collapse due to overfishing, while many wild stocks have collapsed.

The migration routes of salmon are long, extending from the northernmost spawning river, the Tornionjoki River, to the feeding areas in the southern Baltic Sea. These long migration routes expose the salmon to high pressure from fishing and lead to political debates about "who is taking our salmon" between the coastal countries of the Baltic Sea. On the other hand, spatial migration offers a lot of data from various parts of the life cycle of salmon that can be utilized in population dynamics models applied to the Baltic Sea salmon assessments.

2.3 Baltic Salmon Fisheries Management

The Baltic fisheries are controlled by the EU's Common Fisheries Policy [2] and by bilateral agreements between the EU and Russia that aim at ensuring economically, environmentally and socially sustainable fisheries. The management decisions concerning the EU fisheries are made annually. Based on scientific advisories, the European Commission prepares proposals for management measures and the actual regulations are adopted by the Council of Fisheries Ministers. In 1997, new international long-term management goals were agreed upon and incorporated into the Salmon Action Plan [10]. One of the most important goals was to safeguard the wild salmon populations by attaining at least 50% of the potential smolt production capacity (PSPC) in each wild salmon river by 2010. Smolts are juvenile salmon that leave their native river for the feeding migration at the sea. The aim was not easy to implement in practice, as the stock specific PSPCs were poorly known [26].

Thus, the Salmon Action Plan created a need to enhance scientific knowledge about different stages of the salmon life cycle. Because salmon population dynamics are complex and data about most of the stocks are sparse, the only realistic approach for developing the necessary decision tools is Bayesian modeling. Compared to more traditional statistical methods, Bayesian models make it possible to combine relevant data from many sources and integrate their information content with a vast amount of expert knowledge in a probabilistic manner. Such a framework provides both estimates for the historical status of the stock and predictions for future stock development under diverse possible management actions. Thanks to the Bayesian interpretation of their probabilities, one can also answer the essential questions of interest, such as, "What are the probabilities for each stock reaching 50% or 75% of the PSPC in the next four to six years?" Fisheries management decisions must have their desired effect within this time period because salmon stocks have short life cycles.

2.4 Assessment of Baltic Salmon Stocks

In the beginning of the 1990s, Baltic salmon stock assessment was performed using simple spreadsheet calculus without any Bayesian features. One of the problems with such deterministic models is that natural and fishing mortalities are assumed to be known without uncertainty, and that the values chosen have a huge impact on the abundance estimates of the stocks. After Varis and Kuikka [27] first applied Bayesian inference to salmon assessment in the Baltic Sea, the need to distinguish effectively between well-known and poorly-known populations led to the wide application of hierarchical models. Today the scientific advisory on Baltic salmon is entirely based on Bayesian methods. The greatest advantage of Bayesian models compared to the traditional statistical models is that uncertainties in large data sets with lots of variation will be taken into account and be visible in the posterior estimates. Thus, traditional methods that are based on point estimates are considered misleading and dangerous by fisheries scientists familiar with the current methods. When scientific advice is given for the management of the stocks, it is highly important to take into consideration the probability of not reaching management objectives because of certain fishing pressure. This is possible only within Bayesian models.

The objectives of wild salmon fisheries management include ensuring a level of smolt production in rivers that will keep the stocks alive and healthy and, at the same time, enable salmon fisheries. Thus, the main focus of the stock assessment is to predict the near-future development of stocks under alternative management plans. However, in order to undertake this, it is important to acknowledge the high complexity of the salmon life cycle and to model all of the factors that influence salmon survival at different life stages in a biologically justifiable manner. Only by understanding the reasons behind the historic changes in levels of abundance and the uncertainties in the biological processes is it possible to advocate management actions that will both prevent the stocks from collapsing and enable their sensible economic exploitation.

Current salmon stock-assessments are based on describing the population life history using an age-structured state–space model (see life-history model,

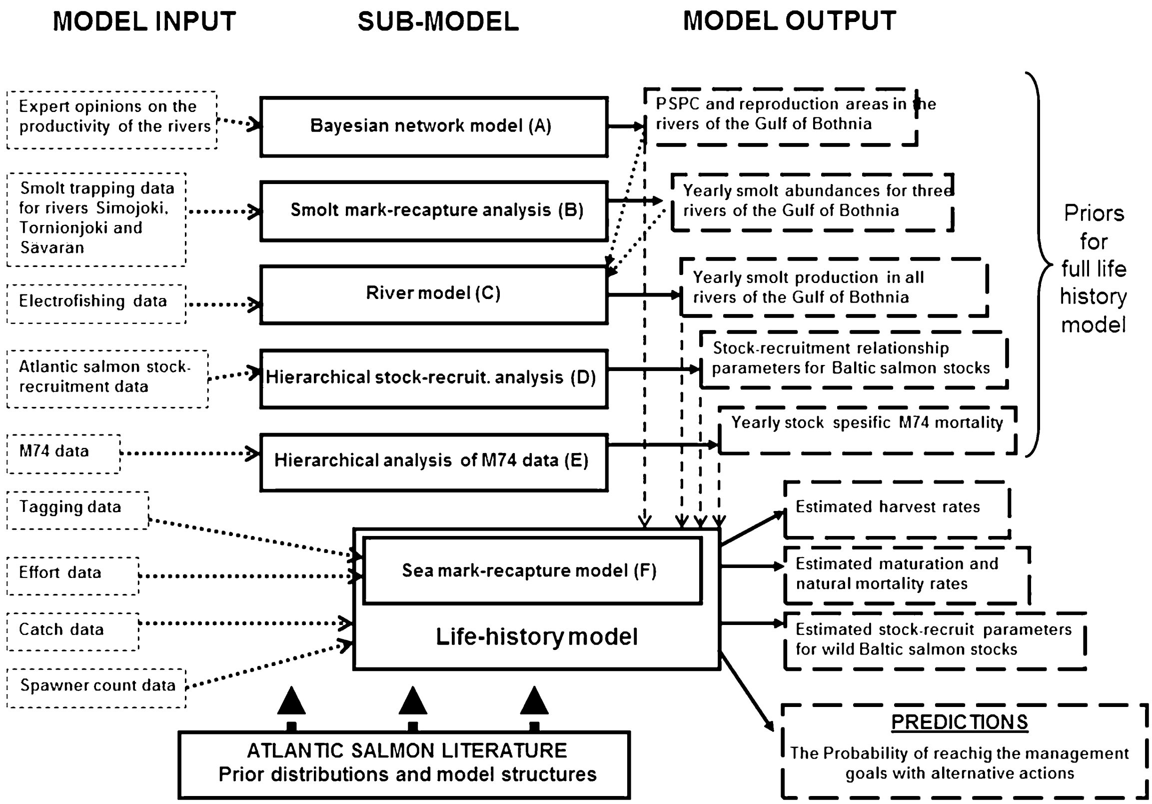


FIG. 2. *The structure of the Baltic salmon assessment model. The most essential blocks of the model are shown in the boxes enclosed by solid lines. The data are illustrated with thin dashed-line boxes on the left and the model outputs with thick dashed-line boxes on the right* [11].

Figure 2) [20]. The state variables describe the temporal and spatial changes in the demography of the salmon population. These include the abundance of wild smolts, $R_{i,t}$, the abundance of salmon in the sea, $N_{i,t,a}$, the spawning population, $S_{i,t,a}$, and the number of eggs, $O_{i,t}$, for each stock i and year t. The subscript a denotes the number of years the salmon have spent in the sea after leaving the river. The model structure and state transitions are described according to existing biological knowledge about the life cycle of salmon, which is illustrated in Figure 1(b). For example, the transition from smolts to the one-sea-year salmon population is controlled by the general relation, $N_{i,t+1,1} = R_{i,t} \exp(-F_{t,0} - M_{t,0})\varepsilon$, where F and M are the instantaneous fishing and natural mortality rates and ε is the process error [21].

The number of eggs produced by stock i is linearly dependent on the stock's spawning population, $S_{i,t,a} = L_a N_{i,t,a} \exp(-F_{t,a} - M_{t,a})\varepsilon$, where L_a is the fraction of the salmon population maturing at sea year age a. The recruitment of new smolts is described by the Beverton–Holt [1] stock-recruit (SR) function $R_{i,t+T} = O_{i,t}/(\alpha_i + \beta_i O_{i,t})$, which describes the relationship between the number of eggs and the abundance of new recruits T time steps later. This function and its parameter values are some of the most important model specifications in fisheries stock assessment, since they determine the predicted impacts of management actions on stock development in the future [18]. Another important factor in Baltic salmon recruitment is early mortality syndrome, M74 syndrome, outbursts of which can kill the majority of juveniles during their first year of life [19].

The inference for the life-history model is performed sequentially, as illustrated in Figure 2 and described by Michielsens et al. [20]. The Bayesian models A, D, E provide prior distributions for the parameters of the life-history model. These prior distributions are based on expert knowledge (e.g., PSPC, A), data from other Atlantic salmon stocks (e.g., parameters of the stock-recruit function, D [18]) or data sets of Baltic salmon that are computationally too heavy to analyze within the full life-history model but can be analyzed separately (e.g., the early mortality syndrome M74 model, E). The posterior distributions of parameters from these models are used as informative prior distributions in the life-history model. The (final) posterior distributions of parameters and state variables are calculated by conditioning on (indirect) observations of the state variables. These data include the time series of catch and effort from different fisheries, spawner count data sets for some rivers, Carlin-tag mark recapture data and data about smolt abundances for a number of rivers. All of the data sets except the last one directly provide likelihood functions for the state variables. Since the observation model for the annual smolt abundances is computationally too demanding, it is approximated as described below.

The data for smolt abundances consist of river-specific smolt mark-recapture data and electrofishing data that contain information about parr (juvenile, 1–4 year-old salmon) densities. The electrofishing data are more often available than the smolt mark-recapture data. First a mark-recapture analysis (model B, [16]) is conducted for rivers with mark-recapture data. These results are then used in a river model (model C, [17]) which describes the relationship between the smolt and parr abundances. The river model is hierarchical over all rivers and, thus, provides smolt abundance estimates for all wild salmon stocks. The posterior distributions of yearly smolt abundances provided by model C are used to construct an approximation for the likelihood function with respect to R in the life-history model [20].

As an example of updating the parameter estimates in the sequential model framework, we illustrate the case of the annual smolt abundance estimates for Tornionjoki River salmon, which is one of the few rivers for which smolt mark-recapture data exist [16]. Figure 3 shows how the estimate of smolt abundance changes in each successive modeling step. The posterior uncertainty is highest after modeling step B, but

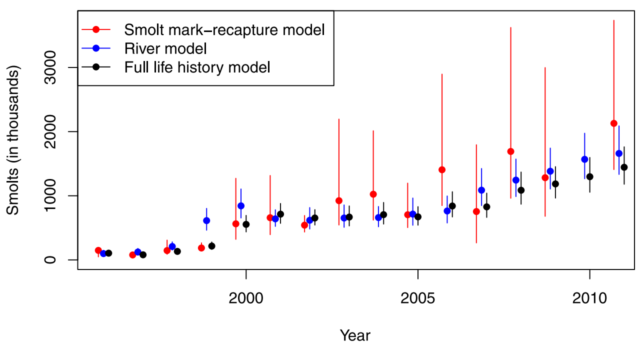


FIG. 3. *The estimate of smolt abundance in the Tornionjoki River after sequential modeling steps B, C and the life-history model shown in Figure 2.*

as data accumulates the posterior distribution becomes tighter. Ideally, we could infer all the models in Figure 2 jointly, but this is not possible with the current computational tools within a reasonable time frame.

3. DISCUSSION

3.1 Why Bayes?

The management problem highlighted above is an example of a problem which could not have been solved efficiently without Bayesian methods. Here we summarize the most important reasons for using Bayes:

- The decision problem is multidimensional. There are several stakeholders with different aims and, thus, the statistical methods used have to allow a detailed decision analysis.
- The life-cycle of Baltic salmon and its response to natural and human induced pressures are complex. Thus, in order to take all the plausible uncertainties into account in decision-making, the stock assessment model needs to reflect the biological realism. This leads to a model with so many parameters that they cannot be estimated without the use of informative priors.
- The available data are multifaceted and there is available essential prior knowledge complementary to data. Thus, the statistical methods must allow hierarchical model structures and the explicit use of priors.
- The precautionary approach incorporated in EU fisheries legislative demands for methods that take explicitly into account all sources of uncertainty.

3.2 Future Scientific Challenges

The greatest current challenges involved in the above example are twofold. First, the computational and technical tasks related to Bayesian inference are complex and time-consuming. Second, it is necessary that the people involved in modeling have a sufficient subject understanding. The selection of model structures, prior probabilities and the likelihood function(s) all depend on subject matter knowledge, in this case biological knowledge. However, researcher's subject matter background easily means that computational problems become overwhelming. It seems that educating methodologically orientated scientists in biology is relatively an easier task than educating, for example, biologists in Bayesian inference.

Although fairly easy-to-use software is available (e.g., OpenBugs or JAGS), much of the time spent by biologically trained scientists is allotted to technical problems related to MCMC algorithms and in waiting for the convergence of runs. This does not represent optimal use of scientific resources. Moreover, because the final modeling is usually based on the outcomes of earlier analysis, and is the last step of a big project, computational problems easily lead to failure in timing.

The Bayesian approach offers a way to formalize scientific learning. The posterior distributions of one study can be used as priors in following studies, if the results are published in a transparent and sufficient way. In fisheries, the risk analyses needed for by-catch species in particular are more or less impossible without meta-analysis [22]. It is necessary to learn more effectively from existing databases and publications and to apply, for example, hierarchical Bayesian models to provide informative priors for case-specific risk analyses and to utilize the correlations of biological features of species in order to make better predictions [13, 23].

The scientific tradition of publishing only "statistically significant" results is a major problem for meta-analysis and systematic learning processes. If only extreme data sets (say, with $p < 0.05$) are published and used in meta-analyses or in scientific discussions, a biased view of the system can be easily obtained. On the other hand, using published papers as a source of prior information in Bayesian models can also create problems when, for example, it is uncertain whether published values are representative samples of the system studied.

The allocation of resources used for data analysis or, alternatively, for the analysis of priors should be an interactive process during scientific projects. If the available data will not be informative enough to make justified scientific and management conclusions, major effort should be directed toward effective and justified derivation of priors. In some cases, this may even be a longer process than a "traditional" data analysis. The collection of new data can be very costly compared to the use of published papers or existing databases [23].

Sometimes it may either be very expensive or difficult to collect data about variables of interest. In such cases knowledge must be elicited from experts. While frequentist methods could be used to (point) estimate some of the model parameters, large parts of the system would be entirely left out from the quantitative analysis owing to complete lack of data. Moreover, Uusitalo et al. have demonstrated [26] that the highest uncertainty in expert knowledge related to salmon assessment comes from the fact that expert opinions differ, and Bayesian inference is needed to integrate those sources of uncertainty. Thus, the classical approach could not provide appropriate answers to the problem of management under uncertainty.

The multifaceted nature of the salmon assessment problem requires use of a complex model, easily leading to thousands of unknown parameters. A vast amount of data with high spatio-temporal resolution would be required to sufficiently identify all of these parameters, if point estimation without prior knowledge was desired. A reasonable maximum likelihood estimation of the main target parameters would require reduction of the model dimensions by effectively assuming that many of the uncertain nuisance parameters were actually known [13]. From the decision-making point of view, this implies that management would then be based on overconfident estimates. While not easy to conduct, the Bayesian approach has made it technically possible to attempt realistic stock assessment, which would currently not be feasible with any other methods.

3.3 Challenges in Applying Bayesian Inference to Practical Scientific Advice

As mentioned earlier, fisheries science is very close to political decision-making and, as in any attempts to model complex systems, there are many subjective choices involved before model-based advice can be given. However, it is far easier for a scientist to defend an analysis when as much data and as few obviously subjective choices as possible have been included. The time available during meetings of stock assessment working groups is often too limited for complex Bayesian models to be applied during the meeting, as the computational inference may easily require a week or more to converge. Thus, transition to Bayesian methods would also demand changes in the practices of the working group in a way that part of the work would need to be done beforehand instead of at the last minute of the meeting.

The need for faster algorithms is obvious, since understanding of the model dynamics and of the logic by which the model operates require practically short calculation time to allow for "what if" type of questions. It is common that in the working groups of fisheries stock assessment the latest data (most recent year on which the predictions are based) can give rise to surprising results. These need then to be discussed and the models adapted accordingly during a very short period of time if the results are to be explained to representatives of the industry and other stakeholders. In some cases this implies that the sensitivity of modeling outputs has to be tested against alternative informative priors. Such sensitivity analyses are critically needed to explain the behavior of complex models to the end users of the information in order to improve their commitment to modeling results [5]. Unfortunately, fisheries scientists are not optimally trusted [4] by industry and improvements in this regard require fully open approaches and learning improved ways to communicate risks. Salmon assessment models are by necessity complex given the characteristics of the life cycle of fishes, but a central goal is nevertheless to make the results more easily understood. When inference algorithms are so slow that only a single run is possible during a week-long working group meeting, the model behavior may not be understood well enough. One approximate solution to this, as is done, for example, in oil spill risk analysis, is to use estimation models and feed the posterior information to a Bayesian network inference engine, which allows an interactive use of the probabilistic results, albeit only approximately [12, 15].

To facilitate general adoption of Bayesian reasoning in risk-averse decision-making, scientists must try to broaden public understanding about risks and the projected consequences of different policies, in a way that is similar to the ongoing debate around climate change. We call for experts in the cognitive sciences to test systematically how uncertainties should be communicated. Such developments will help prevent more man-made fisheries catastrophes such as the arctic cod stock collapse of 1992. Since aquatic resources are in global decline and the situation is already alarming for many ecologically and economically important species, there is more need now than ever for careful Bayesian reasoning to help improve the public's understanding of the risks facing these resources.

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