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Bayesian statistics for fishery stock assessment and management: a synthesis

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Abstract. Bayesian statistical analysis has become an important tool in modern fisheries sciences. We assert that this success is due to the ease in which uncertainty can be explicitly incorporated in inference and decision making. To appreciate the profound conceptual change implied by the switch from frequentist to Bayesian views, it is necessary to understand probability as a wider, more powerful concept: quantification of inductive logic. The advantages resulting for fisheries sciences are examined and illustrated with examples. Some alleged weaknesses of the Bayesian approach are questioned. The important ability and still under-explored potential of Bayesian decision analysis to keep facts and values apart, is also highlighted.

Key words: Uncertainty, plausible reasoning, posterior probability, decision analysis, Pacific cod.

Resumo. Estatística Bayesiana em avaliação e manejo de estoques pesqueiros: uma síntese. A análise estatística Bayesiana tornou-se ferramenta importante na moderna ciência pesqueira. Nós propomos aqui que este sucesso se deve à simplicidade com que as incertezas podem ser explicitadas tanto em inferência quanto na tomada de decisão. Para perceber a profundidade da mudança conceitual envolvida na mudança do enfoque freqüentista ao Bayesiano, é necessário entender a sua concepção mais ampla e poderosa de probabilidade: quantificação de lógica indutiva. As vantagens que derivam disso para as ciências pesqueiras são examinadas e ilustradas com exemplos. Algumas alegadas fraquezas do enfoque Bayesiano são questionadas. A importante, porém ainda sub-explorada, habilidade da análise Bayesiana de decisão em distinguir os fatos científicos de valores e prioridades da sociedade é também destacada.

Palavras-chave: Incerteza, plausibilidade, probabilidade posteriori, análise de decisão, bacalhau do Pacífico.

1- Introduction

The Bayesian approach to statistical inference and decision making has experienced fast growth over the last twenty years in environmental modeling, particularly fishery. Researchers, so far comfortably entrenched within the limits of orthodox (frequentist) statistics, feel that they have to drop the guard and seriously examine this new way of data analysis and statistical inference.

However, this phenomenon entails a paradigm shift and is not free of resistance and criticism. An extract from Dennis (1996) an adversary of the Bayesian way, gives a flavor of the kind of sentiments involved in the controversy.

Bayesian statistics (...) is not just a new set of tools for ecologists to use. It is a whole different way of doing business. Bayesian and frequentist statistics cannot logically coexist. – Dennis 1996

In a more pragmatic tone, Jaynes (2003) suggest there might be no going back.

In this old works there was a tendency, on both sides, to argue on the level of philosophy or ideology.(...). We are now in a position of proven theorems and masses of worked-out numerical examples. As a result, the superiority of Bayesian methods is now a thoroughly demonstrated fact in a hundred different areas. – Jaynes 2003.

A major shift towards Bayesian data analysis in fisheries can be dated back to the works by Hilborn *et al.* (1993) and Ludwig *et al.* (1993), both very critical on the traditional way of doing business in fishery assessment and management. Their diagnostics pointed to the necessity for a full incorporation of scientific uncertainty into the process. The Bayesian approach became a natural choice since it has the tools to: (*i*) display inferences in the form of *posterior* probability distributions, (*ii*) include all relevant information outside the data by way of a *prior* probability distribution, and (*iii*) use Bayesian decision theory to compare and choose among alternative management options.

Frederick & Peterman (1995) presented a formal analysis of the important effects that uncertainty could have on the choice of optimal management actions. They also noticed that the richness of information contained in a *posterior* probability distribution can not be matched by orthodox point estimates or confidence intervals.

These facts and the increasing number of papers using the new approach over the last ten years gave credibility to Bayesian analysis. A good introduction on some of the technicalities of the method directed to practicing fishery scientists was given by Punt & Hilborn (1997).

In our attempted synthesis of the expanding role of Bayesian analysis in fisheries assessment and management, we start in section 2 examining how the principles behind de Bayesian approach affect the philosophy of scientific investigation and contrast it with the orthodox view to facilitate perception of the differences. In section 3 we review basic elements present in any Bayesian inference and decision analysis related to fishery model formulation. In section 4 we discuss some alleged limitations of Bayesian data analysis in fishery sciences. In section 5 some relevant but still under-explored potentialities are examined. A final section with our concluding remarks completes the paper.

2- Probability: the logic of Science

We borrowed the title of this section from the excellent book by Jaynes (2003) who presents probability as plausibility measure of propositions. This extends classical Aristotelian logic, restricted to true (probability 1) or false (probability 0) propositions, to a continuum of possibilities in between. In other words, it involves a change from deductive to inductive logic.

This interpretation of probability is radically different and much more general than the traditional (frequentist) alternative which defines probability as the limit of relative frequencies obtained from repetition of identical experiments. Due to its importance for a clear understanding of the Bayesian approach, we illustrate some aspects of the logic that is involved in plausible reasoning.

Suppose you are told that a given population of bluefin tuna has a sex ratio female:male of 1:1. With this information you can calculate the probability that in a sample of 10 bluefin tuna there will be nine females, and so on. The sort of pre-data reasoning that goes into this calculation is within the framework of deductive logic in which, given a set of premises, consequences can be worked out with certainty.

Most scientists, however, will face the reverse of the above situation and need to answer much harder questions. That is, they will be concerned with post-data reasoning of the following type. Given that in a sample of ten bluefin, nine were female, how plausible is each of the following propositions?

A: the sex ratio of the bluefin tuna population is 1:1

B: the sex ratio of the bluefin tuna population is 3:1

C: the sex ratio is 1:1 but there is a spatial segregation between sexes.

Common sense might suggest that evidence contained in the data make B more plausible than A. However, if knowledge from other known bluefin populations and similar species all suggest a sex ratio of 1:1, and since the sample is small, we might still prefer A over B. But should we argue similarly if, instead of nine females in a sample of ten, we had 90 females in a sample of 100? Although sample size can play an important role in defining relative plausibilities of A and B, these data do not contain relevant information to distinguish B from C, and a still larger sample size will not help.

The type of plausible reasoning exposed in the example is within the general framework of inductive logic and needs to address a difficult question: how much our current plausibility about some proposition should change in light of new information?

If we were able to define a measurement of plausibility, then we would possess a powerful tool to formalize the logic of inductive reasoning in Science. This challenge was overcome successfully by two researchers. First, Pólya (1954 apud: Jaynes 2003) determined that there are just three desirable qualitative characteristics that should be present in any formal representation of plausibility: (1) representation of plausibility by real numbers (i.e., quantification); (2) qualitative correspondence with common sense; and (3) consistence in the sense that no relevant and known information is excluded from the process (i.e. process is non-ideological) and that two analysis using equivalent propositions and the same set of information must lead to the same plausibility value.

Based on Pólya´s qualitative structure, Cox (1961, apud: Jaynes 2003) worked out the quantitative rules for this measurement. Somewhat to his surprise, he found that the *only* rules which met this requirements where those of probability theory. In practical terms this means that, for scientific inference under uncertainty, the calculus of probability is all we need to perform correct plausible reasoning. Working independently, Jeffreys (1961) came to the same conclusions.

Many statisticians dislike this interpretation of probability by arguing that it makes everything subjective. They prefer to think that 'the probability that a fair coin turns out heads is ½' is expressing some intrinsic property of the coin, accessible to (approximate) measurement through experimentation like counting the number of heads in a large amount of repeated and identical throws of the coin.

This frequentist interpretation of probability as the *long-run relative frequency* faces some problems. First, if the act of 'repeated and identical throws' is possible (at least in principle), and if Newton´s laws of physics are valid, then the outcome is predictable with certainty (i.e. deductible). Hence, it seems to be our incapacity of knowing or controlling all relevant variables that go into the trajectory of the coin which make the process uncertain. After all, it seems that probability is no longer a property of the coin but an expression of our partial ignorance about the phenomenon.

A second problem with the frequentist interpretation is the self-imposed and, from a Bayesian viewpoint, unnecessary restriction in the use of probability. Questions like 'what is the probability that current levels of lobster catches are sustainable?' or 'what is the risk of an oil spill on next year's recruitment of some fish stocks?' are nonsense from a frequentist standpoint. However, most relevant questions in fishery management will be of this type and scientists will not stop looking for answers just because their questions remain outside the strict limits of frequentist statistics. Could it be that, deep inside, most scientists reason in a Bayesian way, even if on the surface they might not agree or even be unaware of it?

Probability calculus allows us to quantify the impact of new information on our plausibility reasoning. That is, it tells how to go from the probability of A, denoted $P(A)$, to the updated probability of A after some relevant new data have been observed, denoted $P(A|\text{data})$. This updated probability is referred to as the 'conditional probability of A given the data' and can be very different from the *prior* probabilities $P(A)$. However, probability calculus does not tell what this *prior* probability ought to be (e.g. what number is associated to $P(A)$?). After all, calculations have to start somewhere. There are simple situations like tossing a fair coin, for which this quantification is simple. In general, however, the process is more intricate and various approaches have been proposed. Lindley (1985) devises the "standard urn" as a possible mental measurement device while Morgan & Henrion (1990) describe protocols which were developed for prior probability elicitation. Empirical studies further suggest that experience and training can qualify people in this activity (Brown *et al.* 1994). Uninformative priors in its various forms (Jeffreys, 1961; Berger, 1985; Jaynes, 2003) are always a good start in expressing 'ignorance'. Although *priors* are an ongoing important research topic, the extra-trouble of having to deal with them is a small price to pay in comparison with the power and generality gained from probability as measurement of plausibility. However this topic can get too technical too fast and will not be further explored here.

We close this section quoting an elegant summary by Sir Harold Jeffreys on how the Bayesian paradigm operates.

When we make a scientific generalization we do not assert the generalization and its consequences with certainty; we assert that they have a high degree of probability on the knowledge available to us at the time, but that this probability may be modified by additional knowledge – Jeffreys (apud: Jaynes, 2003)

3 – *Priors*, Likelihoods, *Posteriors* and Utilities

We denote all unknown elements of interest in a problem by H (e.g. the parameters of some population dynamic model). All that is known by X (e.g. observational or experimental data). In a Bayesian statistical analysis we aim at $P(H|X)$, the conditional probability of the elements of interest based on all we know. Bayes theorem provides the calculations.

$$P(H\mid X) = k \cdot L(X\mid H)\cdot P(H)$$

$L(X|H)$ is the likelihood for data X, $P(H)$ the prior probability of H in accordance with all relevant information about H that we bring to the analysis but is complementary to X, and $k = P(X)^{-1}$ a normalizing constant to retain $P(H \mid X)$ within bounds [0,1].

The relative importance of statistical data and *prior* knowledge are well characterized in this expression. As soon as relevant data accumulate, the likelihood will dominate the calculations and estimates will usually approach those obtained in orthodox statistics. However, in limiting situations where orthodox statistics tend to collapse, Bayesian inference continues to give reasonable results. With limited data, the importance of *priors* grows.

If we have a finite set of possible values H_i (i = 1, 2, ...,q) with *posterior* probabilities given as $P(H_i \mid X)$, and we wish to choose among s alternative actions d_j for j = 1, ..., s, then we also should take into account the "utilities" (u_{ij}). These utilities quantify the decision makers preferences among possible consequences that result from combinations of H_i and d_j. A Bayesian decision analysis claims that a rational choice takes as best action one that maximizes the expected utility $\bar{u}_j$.

$$\bar{u}_j = \sum_{i=1}^{q} u_{ij} \cdot P(H_i \mid X)$$

While the calculation of $P(H \mid X)$ corresponds to the stage of the analysis in which uncertainties and risks are formally stated in light of available information, the search for an optimal action (i.e. calculation of expected utilities $\bar{u}$) is a central goal of management.

Within the model structure that is usually used in fishery models or in conservation biology, we translate the elements of Bayesian analysis in very general terms by defining a non-linear and non-Gaussian state-space model. We start by assuming that population biomass evolves in time by some stochastic process

$$b_t = F(b_{t-1}, v_t),$$

in which b_t is the biomass in time t with process noise v_t and some function F describing the temporal biomass dynamic (e.g. Schaefer production model)

The data y_t at time t (e.g. catch per unit effort) are related to b_t by the statistical model

$$y_t = G(b_t, e_t),$$

in which G is some function characterizing that relation and e_t is a random variable modeling observation error.

There are unknown parameters contained in F, G and in the probability distributions of v_t and e_t. The vector with all those parameters is H, while X denotes the vector of observations y_t.

The many ways in which (orthodox or Bayesian) estimates of H have been used in the past can be classified according to the way in which process noise and observation errors are dealt with (de Valpine, 2002). The simplest Bayesian approaches ignore process noise and retain only observation errors (Kinas 1993, 1996, Hilborn *et al.* 1994). The use of only process noise or observation error and the resulting differences are examined with an example by Hilborn & Mangel (1997). The evolution in computational techniques to perform appropriate numerical integration to obtain $P(H|X)$ when H is high-dimensional, made it possible to retain both sources of stochasticity (McAllister & Ianelli 1997).

In formulating the above state-space model b_t or y_t can be multidimensional. For instance, b_t can denote a vector of biomasses for different length (age) classes or for distinct geographical areas. Vectors for y_t can be defined in a similar way. Mutatis mutandis, the components of the vectors b_t and y_t can also denote different species in a multi-species dynamic model.

A common confusion about model parameters is the claim that they are *random variables* in Bayesian statistical inference and *constants* under the frequentist interpretation. For instance, the well known and very enlightening paper by Ellison (1996) errs on this minor detail. In fact, this misunderstanding derives from retaining a frequentist interpretation of posterior probability distributions. As we have seen above, with probability defined as quantification of inductive logic, a Bayesian posterior distribution describes relative plausibilities of different propositions about the fixed, parameter in light of available knowledge.

We finalize this section with an example that gives some appreciation on the richness of information that a Bayesian analysis can entail. In many situations *posteriors* have a single maximum so that some best estimate and associated probability intervals are appropriate summaries and the advantage over orthodox inference is not clear. However, depending of the nature of the data, we can eventually obtain posterior distributions which are multimodal so that the shape of the distribution cannot be summarized by just a couple of numbers. The bi-modal *posterior* displayed in Figure 1 was obtained by Kinas (1993) from a series of 22 years of catch and CPUE data for Pacific cod (*Gadus* *macrocephalus*), using a delay-difference model. The two modes show an unresolved uncertainty between a highly productive but less abundant (r-strategist) or less productive and more abundant (K-strategist) stock. This controversy was, in fact, a point of debate at the time of the analysis. The posterior distribution displays this duality, showing that available data were unable to resolve this uncertainty.

The impact of an informative versus a non-informative prior distribution on the final estimates can be further evaluated with the marginal distributions given in Figure 2. The dotted lines display the same marginal distributions that are given in Figure 1 (b and c), respectively and correspond to the informative prior. If prior is non-informative, the plausibility of a less productive large-biomass stock (K-strategist) reduces although the general bi-modal pattern remains (Fig. 2a). The estimate of equilibrium unfished Biomass becomes less precise determining the range [0, 1] for $\ln(B_1)$ as very probable.

4 – Complexity and Subjectivity

There are two concerns mentioned repeatedly when reference is made to the Bayesian approach in fisheries: the complexity and computational demand that is involved in the use of realistic and high-dimensional probability models, and the unwanted subjectivity of *priors* ‘contaminating’ scientific analyses. We comment on each of these concerns.

Complexity

Many students and scientists are easily attracted to Bayesian analysis at first sight, due to the simplicity and clarity of its arguments. Frustrations tend to show up as soon as a practical problem calls for solution. This is a common trend among researchers in all fields were training in orthodox statistics still dominates, since there has been a tendency to proceed rapidly into advanced statistical methods without spending ‘enough time’ with the basic tools of probability calculus.

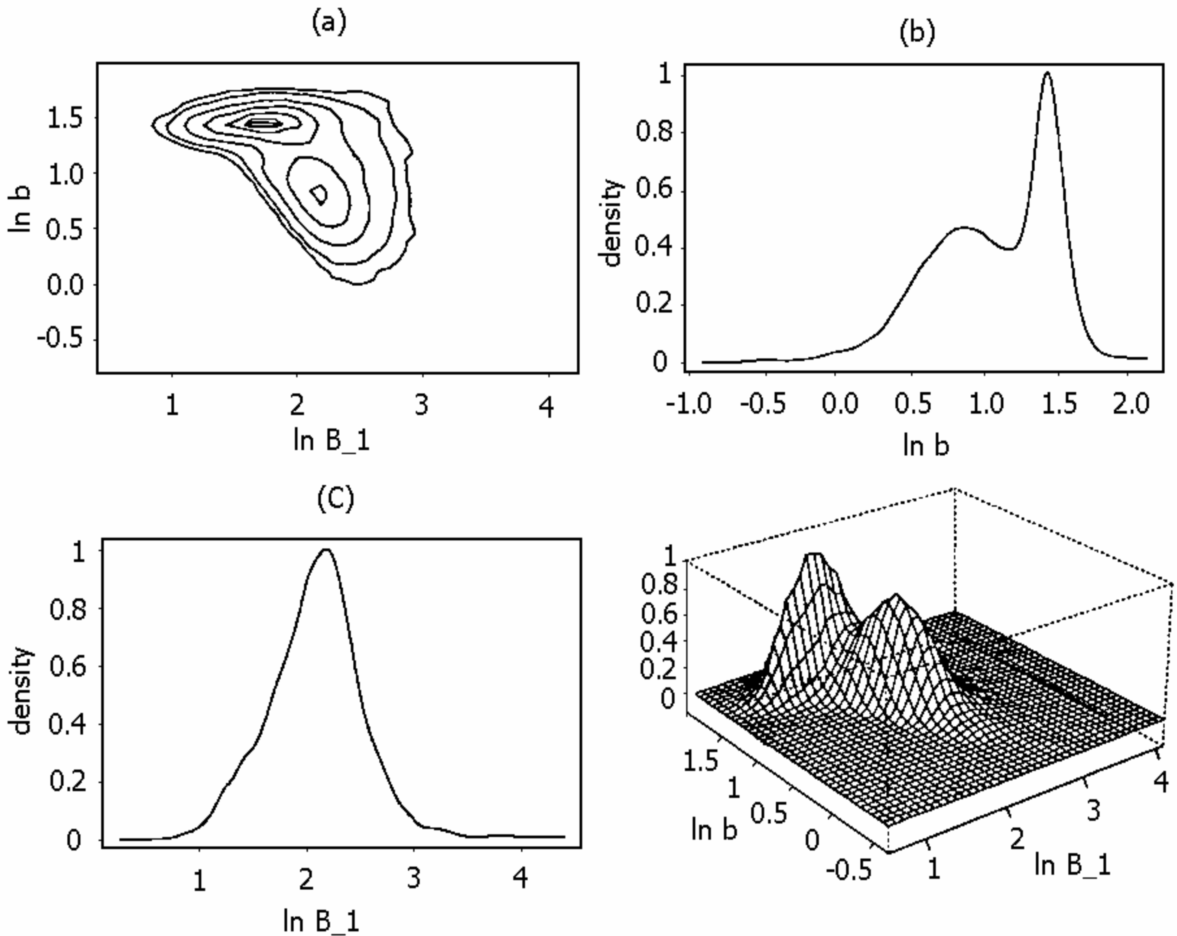

Figure 1: Estimated posterior marginal density for Pacific cod (*Gadus macrocephalus*). B_1 is the unfished equilibrium biomass and b the production parameter from a Ricker stock-recruitment relation and can be interpreted as the ratio B_1/S_{max} where S_{max} is the spawning stock biomass which produces maximum number of recruits. Contours in (a) represent 0.05, .10, .25, .50, .75, .90 and .95 of largest observed density.

We claim that, with just more attention to probability calculus in the training stages, this distortion can easily be corrected.

Another source of frustration is the technical complexity required in some cases to obtain *posteriors*. These difficulties can grow rapidly with increased dimensionality of the parameter vector *H* and non-linearity in functions *F* and *G*. To sidestep these hurdles, the use of demanding stochastic simulations may be necessary (Gelman *et al*. 1995). Good news is that user-friendly and free software like WinBUGS (Spiegelhalter *et al.* 2000) are already available and expanding.

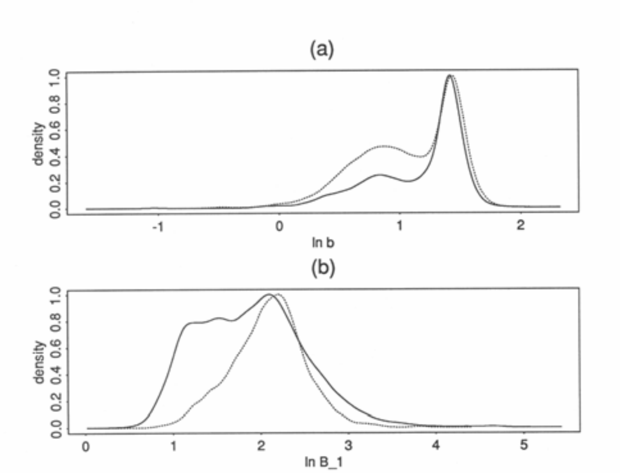

Figure 2: Marginal posterior density for (a) ln *b* and (b) ln B_1 in the Pacific cod (*Gadus macrocephalus*) example. Full and dotted lines correspond to 'non-informative' and 'informative' priors, respectively.

The principle behind stochastic simulation is that *posterior* probabilities can be represented by a large sample of random values simulated according to its distributional properties. In fisheries, the most used procedure has been Markov chain Monte Carlo (MCMC) (McAllister & Ianelli 1997, Schnute *et al.* 2000, Kinas 2002) because of computational efficiency and the growing popularity of software WinBUGS. Other procedures like Sampling Importance Resampling (SIR) (Kinas 1996) and Adaptive Importance Sampling (AIS) (Kinas 1993, Andrade & Kinas, *in press*) seem to be more appropriate where multimodality in the *posterior* is expected, but still need to acquire more computational efficiency and user-friendly display.

The popular Ecopath with Ecosim (EwE) modeling software includes the Ecoranger module which implements a SIR scheme to derive Bayesian *posteriors* for ecosystem trophic mass balance analysis. But, according to Christensen & Walters (2004), these capabilities have been used in only a few examples and still await full exploration.

Subjectivity of *Priors*

The laudable attempt for objectivity in scientific investigation, often downplays *priors* as an unwanted but unavoidable weakness of Bayesian analysis; a source of embarrassment for any serious investigator.

To address this important aspect of any Bayesian analysis, it is appropriate to start asking what we want to achieve when choosing our *prior* probability distributions. We agree with the answer given by Jaynes (2003) who considers any (Bayesian) inference problem as been ill-formulated until three essential aspects about *priors* have been settled:

a) *Prior* probabilities represent available *information* (and not some cloudy believe or guess) and have to be determined by logical analysis of this information and not by pure introspection.

b) Since the conclusions of the study necessarily will depend on available and relevant information as well as the experimental or observational data, it follows that this information should be described with the same level of detail as are the data.

c) Our goal is to make our inference completely 'objective' in the sense that two people in possession of the same information would come up with the same *priors*.

We quite naturally take zero as the starting point for any summation of a column of real numbers. Similarly, non-informative *priors* are often a natural start in any practical Bayesian analysis (Berger 1985). Jaynes (2003) makes a strong argument in favor of 'maximum entropy priors' as an objective criterion to define informative *priors* which maximize ignorance beyond any known constrains; is seems a very promising direction for further research.

Hence, the 'subjectivity' of all probabilities, as advocated by Bayesians, relate to the fact that probabilities are always a consequence of available information and not some arbitrary quantification. Finally, it is important to highlight that scientific judgment is necessary when deciding about *priors* as much as it is necessary to decide about data models (i.e. likelihoods). Therefore, there is no reason to restrict this onus to *priors* only. When analyzed in this larger context we might see *priors* more as strength and not as weakness, after all.

5 – Under-explored Potential in Fishery Models

In the context of fisheries modeling there are particularly two under-explored possibilities which we like to highlight: (*i*) incorporation of model uncertainty and (*ii*) an extended use of Bayesian decision analysis to support managers in the difficult task of multi-criteria decision making in presence of uncertainty.

It is a platitude among modelers of complex biological systems to recognize that there is no 'true model' which we try to identify. All models are idealized simplifications of reality although some will be more useful than others. As soon as we give up our search for the true model, we find ourselves asking a more relevant question: 'Does the candidate model´s deficiencies have a noticeable effect on the substantive inference?' (Gelman *et al*. 1995)

Since limited data usually will agree with various structurally different models, we need a strategy to rank them in some fashion. Burnham & Anderson (2002) use criteria from information theory like *Akaike information criteria* (AIC) and *Bayesian information criteria* (BIC). These criteria rank models by establishing some compromise among goodness-of-fit and model complexity. Once a finite number of distinct models m_k (k = 1, ..., M) has been defined, analysis proceeds after choosing the best among candidate models or by using all models in multi-model inference with weights according to the chosen classification criteria.

In Bayesian inference, model weighting is done by way of *posterior* probabilities $P(m_k | X)$ for k = 1, ...,M. Burnham & Anderson (2002) show that the use of AIC or BIC as weighting criteria is equivalent to the choice of particular *priors* over all M models. In particular, BIC assumes a uniform prior among all M models while AIC assumes a less intuitive prior distribution. Hence, from a Bayesian perspective, the choice between AIC and BIC is equivalent to choosing among these *priors.*

An alternative criterion proposed exclusively to classify Bayesian models is the *deviance information criteria* (DIC) (Spiegelhalter *et al*. 2002). This criterion seems to have advantages over AIC and BIC when dealing with Bayesian hierarchical models and is furthermore easy to calculate as by-product in MCMC.

A Bayesian model is hierarchical whenever there is a known structure in the parameters so that priors can be decomposed in two or more stages. As an example, take y_i as the catch per unit effort in some region i with true (unknown) abundance H_i, modeled with likelihood $L(y_i|H_i)$ and *prior* $P(H_i)$ in order to obtain the *posterior* estimate of abundance $P(H_i|y_i)$. If there is some known structure among abundance in different regions, then it can (and should) be used to improve de prior on H_i by incorporating it as a probability model $P(H_i|\eta)$ together with a second stage "hyper-prior" $P(\eta)$. The hierarchical structure is nothing but a convenient way of representing prior information whenever there is qualitative information available to do so or when data themselves present a hierarchical structure.

If there are good arguments in favor of the Bayesian approach in fisheries assessment, we believe that its advantages shine even brighter when we focus on the comparison of alternative actions and the process of decision making under uncertainty. Once all options are structured within the formalized framework of Bayesian decision theory (Berger 1985, Lindley 1985), three advantages can be identified.

The first advantage is the effective and complete incorporation of scientific uncertainty into the decision process, made operational through the *posterior*. This intent is no longer a rhetorical and ill-defined objective as often seen in practice. The relevance of uncertainty in the political game among stakeholders should not be underestimated when it comes to resource management. An insightful example is the documented history of the changing role played by uncertainty within the International Whaling Commission (Heazle 2004).

A second advantage derived from this formalization is the effective distinction between scientific facts (present in the *posterior*) and the perceived values of potential consequences (measured with utilities or losses). This clear distinction between scientific responsibilities and preferences elected by society can, at least in principle, facilitate dialog and negotiation among stakeholders.

The third advantage is the pedagogical exercise pointing out that:

(*i*) it only makes sense to talk about 'good' or 'bad' management actions when we have two or more alternatives to compare.

(*ii*) since the selection of some 'best' alternative depends on both, *posterior* and utilities, changes in at least one of these components can change choices without being inconsistent with the general decision process. Furthermore, Bayesian decision theory tells quantitatively how strong these changes ought to be.

(*iii*) the transparency of the decision process embedded in a Bayesian decision analysis not only facilitates communication among contenders and with the general public, but also serves the learning process since mistakes and successes can be tracked back and hopefully understood.

Although advantages of Bayesian decision analysis are easy to identify, the use of these tools to support decisions is still rare in Brazil (Vasconcellos 2003, Andrade & Kinas, *in press*) and should be encouraged.

There is some overlap of Bayesian decision analysis with recent developments of Operational Management Procedures (OMPs) (Kell *et al.* 2006) and Management Strategies Evaluations (MSEs) (Arandas & Motos, 2006). For instance, a 'performance statistic' described as key elements in OMPs, correspond to a simplified version of the more general concept of utilitiy, u_{ij}. Utility is more general because it measures performance on a probability scale which allows incorporation of important behavioral characteristics like risk-aversion. We think, however, that OMPs provide useful tools which can help to make Bayesian decision analysis more operational in fisheries management. Conversely, Bayesian decision analysis can provide a solid theoretical structure to guarantee consistency in the decision process. For instance, the universality and simplicity of expected utility as criterion to choose among alternative decisions, is an important theoretical results from Bayesian decision analysis and should not be ignored.

Multiple conflicting objectives, communication among stakeholders and scientists, incorporation of 'user knowledge', all are elements of concern in MSEs, as much as they have been in Bayesian decision analysis for more than 20 years (Lindley, 1985). It would be highly desirable if practical experiences gathered from management via MSEs and OMPs could help to make Bayesian decision analysis easier to implement.

6- Conclusion

The present work is not a review paper and therefore not aimed at an exhaustive compilation of the literature available on the subject. Cited articles were selected to complement and illustrate the text.

As concluding remarks to this synthesis about Bayesian approach in assessment and management of fisheries there are four points we wish to highlight. First, it is worthwhile to notice that the Bayesian interpretation of probability is much more general then the frequentist alternative. While the latter restricts probabilities to the limit of relative frequencies of events replicated under identical conditions, the Bayesian defines probabilities as a plausibility measure of propositions which includes the frequentist interpretation as a very special case. This distinction is important for an appropriate interpretation of a Bayesian data analysis.

Once the interpretation of probability is taken into consideration, our second point is to express all uncertainties in the posterior probability distribution $P(H|X)$ which is a synthesis of all information (data and otherwise) currently available. Hence, the *posterior* is the central element for statistical inference based on which any question of interest about H should be addressed.

Thirtly, we remind the reader that the relevance of prior probability distributions depend on the quantity and quality of hard data. Whenever a large amount of informative data is available, Bayesian and orthodox inference will give very close answers. Differences become more pronounced with insufficient data since the relevance of *priors* becomes more critical. With an appropriate understanding of the purpose of formalized *priors*, we claim that this is a strength and not weakness of the Bayesian approach.

At last, the formal structure of a Bayesian decision analysis is adequate to address natural resource management because it facilitates communication among contenders and distinguishes scientific uncertainties (facts) from preferences (values). This distinction is important because both, facts and values, play important but distinct roles in any decision process.

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