# A framework to put in practice a precautionary approach to fisheries assessment based on fuzzy set theory.

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## 1 Introduction

The motivation for this work came from the observation that although a precautionary approach to fisheries is being followed in the northeast Atlantic fisheries, it has been only partially implemented. In fact, it is hard to find examples of stock exploitation being restricted on the basis of ignorance about the state of the stock, whereas examples of resources being highly exploited despite the lack of scientific knowledge on their state and dynamics are much easier to find (e.g. deep-sea fish off Portugal, Figueiredo pers. comm.). This *status-quo* can be explained by several factors, such as deficiencies in dealing with stock assessment uncertainties, difficulties in communicating those uncertainties to fisheries managers and deficiencies in the definition and implementation of management rules and targets.

The purpose of this paper is to put in evidence shortcomings still existing in handling uncertainty in the assessment process, and to present an example of a framework based on fuzzy set theory to help fisheries managers to define management rules and targets, and at the same time to help fisheries scientists to provide advice according to those targets and dealing with the assessment uncertainty.

# 2 Precautionary approach

The adoption of a precautionary approach to fisheries assessment and management implies that "a lack of full scientific certainty must not be used as a reason for postponing cost-efective measures to prevent environmental degradation" (principle 15 of the Rio de Janeiro Declaration; FAO, 1995). To apply the precautionary approach several tasks should be accomplished, such as the establishment of management objectives, the specification of the information needed, the assessment of the state of the stock putting in evidence all sources of uncertainty, and the definition of rules for management decisions, which should be robust to uncertainty and to incomplete knowledge on factors such as stock identity and dynamics and the effects of environment (FAO, 1995).

Uncertainty is without doubt a key concept when implementing the precautionary approach. Although there are many possible ways to account for uncertainty in fisheries assessment (Patterson et al., 2001), these are not used in most stock assessments carried out within ICES working groups. Instead, the outcome of the assessment (that is, the advice given to managers) is expressed in terms of the situation of the stock regarding certain reference points or with a statement about probabilities of the stock attaining certain states, which just take into account a small fraction of the assessment uncertainty and are therefore misleading. Therefore, the implementation of the precautionary approach in many stock assessments seems to be not focused enough on chosing alternatives to tackle with uncertainty and to incorporate it in the best way in the advice given to managers.

# 3 Sources of uncertainty

Francis and Shotton (1997) have classified the sources of uncertainty in fisheries assessment and management into 6 types:

1. Process uncertainty: the one that arises from natural variability. This kind of uncertainty is the only one considered irreducible (Fogarty et al., 1996), because cannot be reduced with increased effort on sampling or scientific research.

2. Observation uncertainty: the one due to measurement or sampling error, can in certain cases be estimated using proper sampling or experimental designs (e.g. variation in fish age determination by otolith reading).

3. Model uncertainty: the one due to ignorance about the system to be modeled or to error for chosing a wrong model. Methods to reduce this type of uncertainty have been proposed by Schnute and Hilborn (1993) and Buckland et al. (1997). Schnute and Hilborn (1993) developed a method to formulate likelihood functions that combine an informative model, supposed to describe well the system, and another model which does not have the parameters of biological interest (such as a kind of "black-box"). Probabilities are attributed to each of these models and a sensitivity analysis to those probabilities may indicate how well the 1st model describes the system. This method can also be applied simultaneously to several data sets that present contradictory trends, being in that case also useful in reducing uncertainties of type 2 (above). Buckland et al. (1997) describe a framework to incorporating model selection bias into inference, by giving weights to different contending models and using a bootstrap procedure to account for model selection uncertainty.

4. Estimation uncertainty: this is a combination of any of the 3 types described above and is what prevents the model from fitting exactly to the data. In most cases it is not possible to say how much of this uncertainty can be attributed to any of the 3 sources described above. However, when there is previous knowledge on other sources of uncertainty, such as those due to sampling or natural variation, it is possible to account for it in the estimation process using Bayesian or Monte Carlo methods (e.g. McAllister et al., 1994; Patterson et al., 2001). A problem common to both approaches is how to account for uncertainty due to parameters for which there is no previous knowledge, or how to chose noninformative priors, in Bayesian terminology (Gelman et al., 1995). In fact, the usual attribution of an uniform probability distribution function to parameters that cannot be estimated from the data and for which there is no previous knowledge (e.g. McAllister et al., 1994) does not seem useful to describe uncertainty in the outcome of the model, especially when parameters are highly correlated, as is the case of fishing and natural mortalities in VPA. Moreover, the implications of this practice are not easily explainable to fisheries managers without training in statistical science.

The 5th and 6th types are "implementation uncertainty", which has to do with the degree and success of implementation of agreed management measures, and "institutional uncertainty", such as the one arising from the lack of well defined management goals.

Dealing with uncertainty in management options has been also object of concern: Hilborn et al. (1993) propose the use of decision tables, and FAO (1995) proposes the use of the "Minimax" and "Maximin" criteria to guiding decisions based on those tables. Hauge (1998) suggest "pedigree matrices" (Funtowicz and Ravetz, 1990) as a way to present the quality of research to fisheries managers.

Personal experience is a factor to take into account in fisheries assessment, especially when dealing with uncertainty. It is common practice in stock assessment to give different weights to different data sets (e.g. CPUE time series), based on empirical experience that indicates some data sets as describing better the evolution of the stock than others. This is a typical example of using personal experience to deal with uncertainty of type 2 (above). Hauge (1998) provides examples of similar decisions taken in real stock assessment work. This kind of decisions should be described objectively and accounted for in the assessment uncertainty.

# 4 Fuzzy sets

Fuzzy set theory was founded and initially developed by Zadeh (1965), based on the idea of sets to which elements could belong with variable grades of membership, between 0 and 1. A soft introduction to fuzzy sets and fuzzy logic is given by Sangalli (1998). Fuzzy sets differ from the classic (or "crisp") ones because in the latter, elements can either belong or not belong (meaning, can only have grades of membership 0 or 1). Hence, fuzzy sets are a general case that include also the classic ones. The idea of fuzzy sets is appealing because mimics the functioning of the human brain.

For instance, the classification of a fish stock biomass as being "high" is the same as saying that that stock belongs to the fuzzy set of "stocks with high biomasses". However, the criterion to classify the biomass of a fishl stock as "high" is a subjective one. The way to put it objectively is to define a membership function that gives to fish stocks with biomass $x$ a grade of membership $y$ to the set of "fish stocks with high biomasses" (see Figure 1). To allocate a fish stock to the set of "stocks with high biomass" with a grade of membership $y$, can be seen as equivalent to give a degree of credibility $y$ to the statement "this stock has a high biomass". The definition of membership functions is a crucial, and

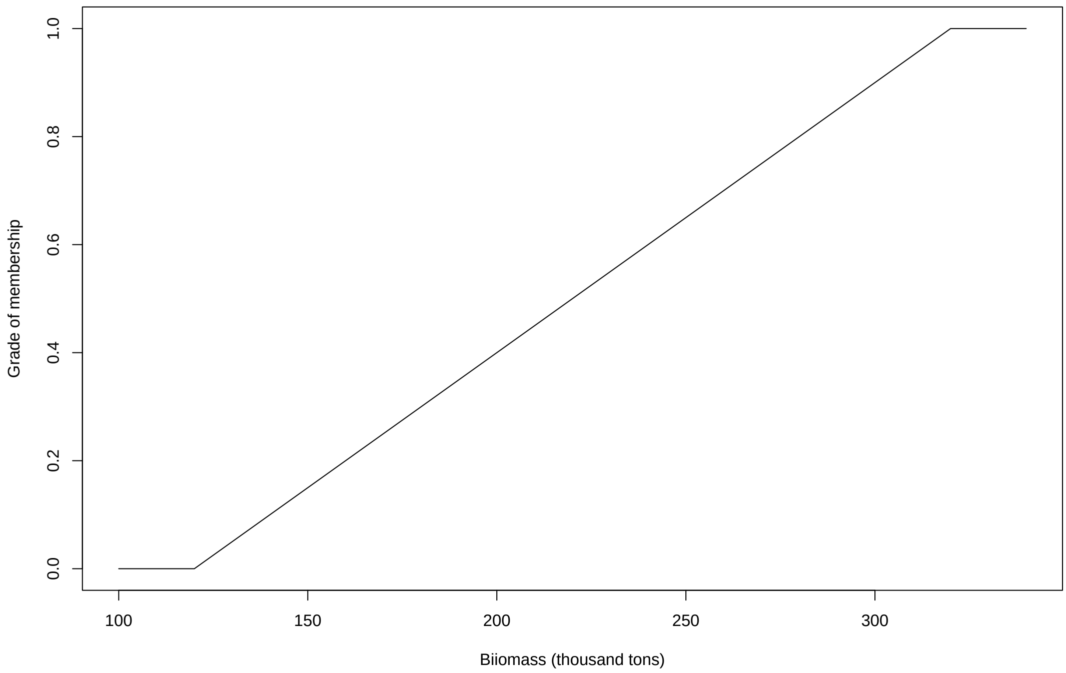


Figura 1: Example of a membership function for the fuzzy set of “fish stocks with high biomass”.

sometimes difficult, task when applying fuzzy set theory. In this example, it is obvious that different fish species should have different membership functions. This example shows that fuzzy set theory can be used to treat subjective concepts in an objective way.

Sometimes, the degree of credibility of a statement (or grade of membership to a fuzzy set) cannot be obtained from a membership function, because no variables can be measured. A typical example in fisheries assessment is to say how well-delimited is a stock. Unless there are previous studies on stock identification and exchange rates of individuals with neighbouring stocks, a membership function to allocate a certain stock into the fuzzy set of "well-defined stocks" will be impossible to obtain. However, personal experience and empirical evidence on how well the stock is defined can be taken into account by attributing directly a grade of membership to the stock without using a membership function. In such a case the experienced researcher could say, for example, that a given stock as a grade of 0.7 of being well defined. This is usually called a "fuzzy input".

# 5 Fuzzy precautionary approach

Most advice given to fisheries managers goes in the form of a TAC, which is based on the values of several characteristics, such as abundance, fishing mortality, recruitment potential, and environmental factors. The TAC is obtained by applying rules, which may be either crisp or fuzzy. A typical crisp TAC might be determined by a mathematical rule such as $F_{0.1}$, or, more simply, something like TAC=0.4×Biomass. Expressed as a rule, this is:

If TRUE then TAC = 0.4×Biomass

(note that TRUE means that the rule is always applied). A slightly more sophisticated (and conservative) example would be:

If Biomass $<$ Threshold then TAC = 0

If Biomass $>$ Threshold then TAC = 0.4×Biomass

Fuzzy rules convey the same ideas crisp rules, but the formulation is in broader terms and the quantification comes at a later stage of the analysis. Corresponding fuzzy rules could be:

If Biomass is LOW then TAC = 0

If Biomass is HIGH then TAC =0.4×Biomass

Then to quantify the model we could define the sets HIGH = (Biomass > Threshold) and LOW = (Biomass < Threshold), and we end up with the same result, since we have a sharp boundary between HIGH and LOW.

However, if we define the sets as HIGH = (Biomass > 1.2 × Threshold) and LOW = (Biomass < 0.8×Threshold) then the sets do not include the range between 0.8×Threshold and 1.2×Threshold. This is the fuzzy range and can be represented by interpolation, so that Biomasses in this range correspond to a combination of HIGH and LOW sets. For example, if Biomass is right at the Threshold (Biomass = Threshold), then it is 50% HIGH and 50% LOW, so the TAC would be 0.2×Biomass by averaging.

The same analysis can be applied to all other variables, and they do not have to be treated independently. For example, the definition of "high mortality" could depend on the size and age structure of the stock. When we have a set of different fishery characteristics, the fuzzy rules take the form

> If Biomass is HIGH and Environment is FAVOURABLE and Compliance is GOOD then TAC can be LARGE

Of course this does not produce a numerical value, so the next step is "defuzzification", which is the process of obtaining crisp quantitative results from fuzzy models. Several fuzzy descriptions of the TAC need to be quantified, including LARGE and SMALL (note that intermediate values can be described as combinations of LARGE and SMALL). The procedure then is to use fuzzy characterisation of the state of the fishery (formulating membership functions for all fuzzy sets) to develop and evaluate the rules, and then to defuzzify the results to generate (or recommend) management decisions.

The examples given above of the formulation of fuzzy harvest control rules, can also account for the uncertainty in the assessment, in accordance with the precautionary approach. Taking as example very simple harvest control rules, such as

> If Biomass is HIGH and Uncertainty is LOW then TAC will be LARGE

the first step would be to define membership functions for Biomass, Uncertainty and TAC. For the latter two, that would be more or less straightforward, using previous information on the stock dynamics and evolution, and by comparison with other stocks of the same species. Regarding Uncertainty, that would have to take into account all sources of uncertainty described in section 3. This could be done by replacing Uncertainty with a fuzzy set for each sorce of uncertainty, changing the 1st rule above into, e.g:

> If Biomass is HIGH and Sampling is GOOD and Recruitment Variability is LOW and Assessment Model is Adequate and (so on...) then TAC will be LARGE

The next step would be to obtain membership functions for all fuzzy sets (the sets of "adequate assessment models", "good sampling of catches", "stocks with high biomass", etc). There are many ways to formulate these functions depending on the source of variability and on how it was accounted for. For example a membership function for the set of "adequate assessment models" could be obtained from the estimates of uncertainty due to model choice given by the methodology of Buckland et al. (1997); for catch sampling, and taking as sampling unit the landings by port, month and gear, the membership function could be the proportion of these units that were sampled in the assessment year; and so on.

# 6 Final remarks

A major advantage of this approach is that the structure of the management model is based on knowledge about how the system works, and not on existing data, which may be based on an inadequate experimental design or distorted by the difficulty of measuring certain variables. For example, one of the fuzzy rules given above includes Compliance, which was identified as important in the discussions of Group 3, but is virtually impossible to quantify. It also can be used to deal with environmental factors which may be imperfectly understood but for which reliable correlations are not yet available, such as the impact of predators or turbulence effects.

As complexity of a system increases, precision of the knowledge about the system decreases. Therefore in very complex systems approximate solutions are needed. For example the statement found in certain interpretations of medium-term projections "there is a probability of 0.64 that the SSB will decrease below $B_{pa}$ in 5 years from now" is misleading in its apparent precision. To say "SSB is very likely to decrease below $B_{pa}$" would be more honest because does not give the impression that a precise probability could be calculated.

Fisheries assessment and advising fisheries managers is a complex decision support system, too complex to be modelled in a classic way with satisfactory results, therefore fuzzy set theory may have an important role to play there. Moreover, a framework such as the one presented here assumes that the "If ... then ..." rules are formulated in cooperation with fisheries managers, allowing them to deal with assessment uncertainty, which does not happen in the current practice (e.g. Hilborn et al., 1993).

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