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A fuzzy-logic tool for multi-criteria decision making in fisheries: the case of the South African pelagic fishery

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Abstract. The present study presents an electronic decision-support tool that uses a fuzzy-logic model of expert knowledge to assist in multi-criteria decision-making in the context of an Ecosystem Approach to Fisheries (EAF). The prototype model integrates the multiple goals and objectives related to the evaluation of the ecosystem performance of the South African sardine *Sardinops sagax* fishery into a NetWeaver knowledge base and provides intuitive visual outputs to communicate results to managers and stakeholders. The software tool was developed in a consultative process with key experts and follows the hierarchical tree approach recommended in the FAO guidelines for responsible fisheries. Input variables are based both on quantitative data and expert opinion. We evaluated the model in terms of robustness to input changes, influence of system structure, and appropriateness of input scales for parameters based on expert opinion. Results show that the model is robust and conservative. The strength of the approach lies in the ability to include variables that are difficult to measure. It provides a means of rendering value judgements explicit and transparent. The tool synthesises a large amount of information and aims at improving understanding rather than achieving precision. The system has the potential to have wide application in the context of EAF.

Additional keywords: Ecosystem Approach to Fisheries (EAF), fisheries management, multi-criteria decision analysis (MCDA).

Introduction

Following the 2002 World Summit on Sustainable Development (WSSD), signatory nations are required to develop and implement an ecosystem approach to fisheries (EAF) by 2012 (Garcia and Cochrane 2005). EAF aims to achieve the collective sustainability of all uses and impacts on an ecosystem. Consequently individual issues cannot be addressed independently because attempts to manage any one issue are likely to have impacts on other issues. Each possible management action has costs and benefits, not only in the financial sense but also in ecological, social and political terms. It is therefore necessary to address all objectives together as far as is practical, and guidelines have been developed to make EAF operational (FAO 2003).

In southern Africa a regional EAF project was launched in 2004, under the auspices of the Benguela Current Large Marine Ecosystem Programme. It includes participation by researchers and managers from Angola, Namibia and South Africa, and addresses EAF implementation from both national and regional perspectives. Ecological Risk Assessments (ERA) have been undertaken for selected fisheries (Nel *et al*. 2007) based on the method developed for Australian Fisheries (Fletcher *et al*. 2002; Fletcher 2005). The ERA identified the major issues related to EAF for each fishery that are not adequately addressed by present management strategies. Although statistical methods and modelling can be used to evaluate the effect of management scenarios in the southern Benguela region (Shannon *et al*. 2004), in many cases the necessary data are not available or the issues are not conducive to evaluation through modelling. In such cases it is necessary to rely on common sense and expert opinion.

Electronic decision-support tools can help to guide managers in situations characterised by uncertainty. In particular, fuzzy logic (Zadeh 1965) has been promoted to deal favourably with uncertainties in our understanding of aquatic systems (e.g. Mackinson 2000; Cheung *et al*. 2005) and provide a rigorous approach for including variables for which quantitative data are not available (Miller and Saunders 2002; Paterson *et al*. in press). Furthermore, fuzzy logic potentially provides an elegant solution in information-rich contexts by avoiding a possible proliferation of rules in an attempt to accurately represent the data (e.g. Miller and Saunders 2002).

Fuzzy logic is based on the concept of the fuzzy set (Zadeh 1965). The boundaries of a fuzzy set are not sharp; the transition between set membership and non-membership is gradual rather than abrupt. Elements that are considered marginal or

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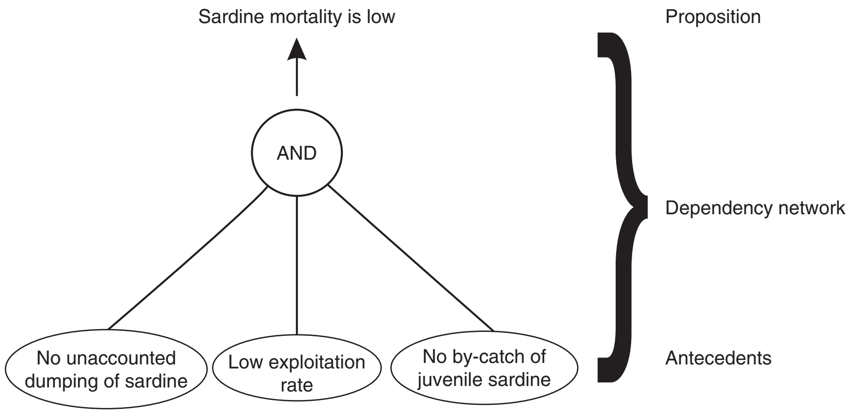

Fig. 1. Structure of a dependency network in NetWeaver, which evaluates the trueness of the proposition ‘sardine mortality is low’. A truth value is generated based on the truth values of the three antecedent networks ‘no unaccounted dumping of sardine’, ‘low exploitation rate’ and ‘no by-catch of juvenile sardine’.

intermediate are given a degree of membership between 0 (non-membership) and 1 (membership). Thus, instead of only two truth values (true and false) fuzzy transformations provide a continuous measure.

The present study introduces the prototype of an electronic fuzzy-logic decision-support tool for monitoring and evaluating the implementation of EAF for the South African sardine fishery (EAF monitoring tool). The prototype was evaluated with respect to sensitivity towards model input and model structure.

The pelagic fishery targets mainly sardine *Sardinops sagax* and anchovy *Engraulis encrasicolus*, and to a smaller extent red-eye round herring *Etrumeus whiteheadii*. In terms of volume of landings, the fishery is the largest in South Africa and the second most important in terms of value. The industry employs ~7800 people. The fishery is currently managed in terms of an Operational Management Procedure (OMP) as described in Fairweather *et al*. (2006*a*). Anchovy and red-eye round herring are fished for reduction purposes, whereas sardine are mainly fished for consumption. After a period of very low abundance in the 1960s, sardine have been managed conservatively since the early 1980s to allow rebuilding of the stock. High biomass has been observed since the late 1990s.

Materials and methods

Software

The EAF monitoring tool was implemented using NetWeaver, a knowledge-engineering platform for the development and maintenance of fuzzy-logic knowledge bases (Miller and Saunders 2002). The primary structural element of a NetWeaver knowledge base is a dependency network, whose function is to evaluate a proposition (Reynolds *et al*. 2000). The truth-value of a network expresses the degree to which the proposition is true, based upon its premises. In NetWeaver the level of trueness is expressed as values between -1 (100% false) and $+1$ (100% true). In the case of missing data 0 is returned, that is the level of trueness is undetermined. For example, the trueness of the proposition ‘low sardine mortality’ is evaluated in terms of its antecedent propositions ‘no unaccounted dumping of sardine’, ‘low exploitation rate’ and ‘no by-catch of juvenile sardine’ (Fig. 1). These propositions are, in turn, evaluated in terms of their antecedent propositions and so on. A NetWeaver knowledge base is thus a hierarchical network of propositions (Fig. 2). At the lowest level input data are transformed based on fuzzy input variables in order to generate a truth value (Fig. 3). For instance, the fuzzy variable low exploitation rate (Fig. 3*d*) returns positive truth values when input values for exploitation rate are below 0.4, with 0.2 (exploitation rate) returning 100% true. When input values for exploitation rate are above 0.4 the proposition is evaluated as false, with inputs greater than or equal to 0.55 (exploitation rate) returning 100% false. When exploitation rate is 0.4 the proposition is neither true nor false.

Individual dependency networks are combined by nodes that represent mathematical operators. In the case of the EAF monitoring tool all input variables and networks of propositions are connected by AND nodes. NetWeaver AND nodes use fuzzy logic to handle uncertainty. Traditionally the value of a logical AND is true if all antecedents are true, and false if at least one antecedent is false. However, if none of the antecedents is completely false, NetWeaver calculates the value of AND as follows:

$$\text{AND (a)} = \text{MIN (a)} + [\text{AVERAGE (a)} - \text{MIN (a)}] \times [(\text{MIN (a)} + 1)/2]$$

MIN (a) is the minimum truth value of the antecedents and AVERAGE (a) is a weighted average of the truth values of the AND node’s antecedents. If one of two antecedents of the same network returns 100% false, the network will always evaluate to false, irrespective of the truth value of the other antecedent. The fuzzy AND is designed to produce a conservative estimate when uncertainty is high. The closer to 0 a truth value is, the greater is the uncertainty regarding the trueness or falseness of the associated proposition. In the case of missing data, the truth value generated by the fuzzy variable is 0. There is thus a penalty for uncertainty, which prevents the AND node evaluation from being overly optimistic (Miller and Saunders 2002). NetWeaver models are hierarchical. There is no limit to the number of layers

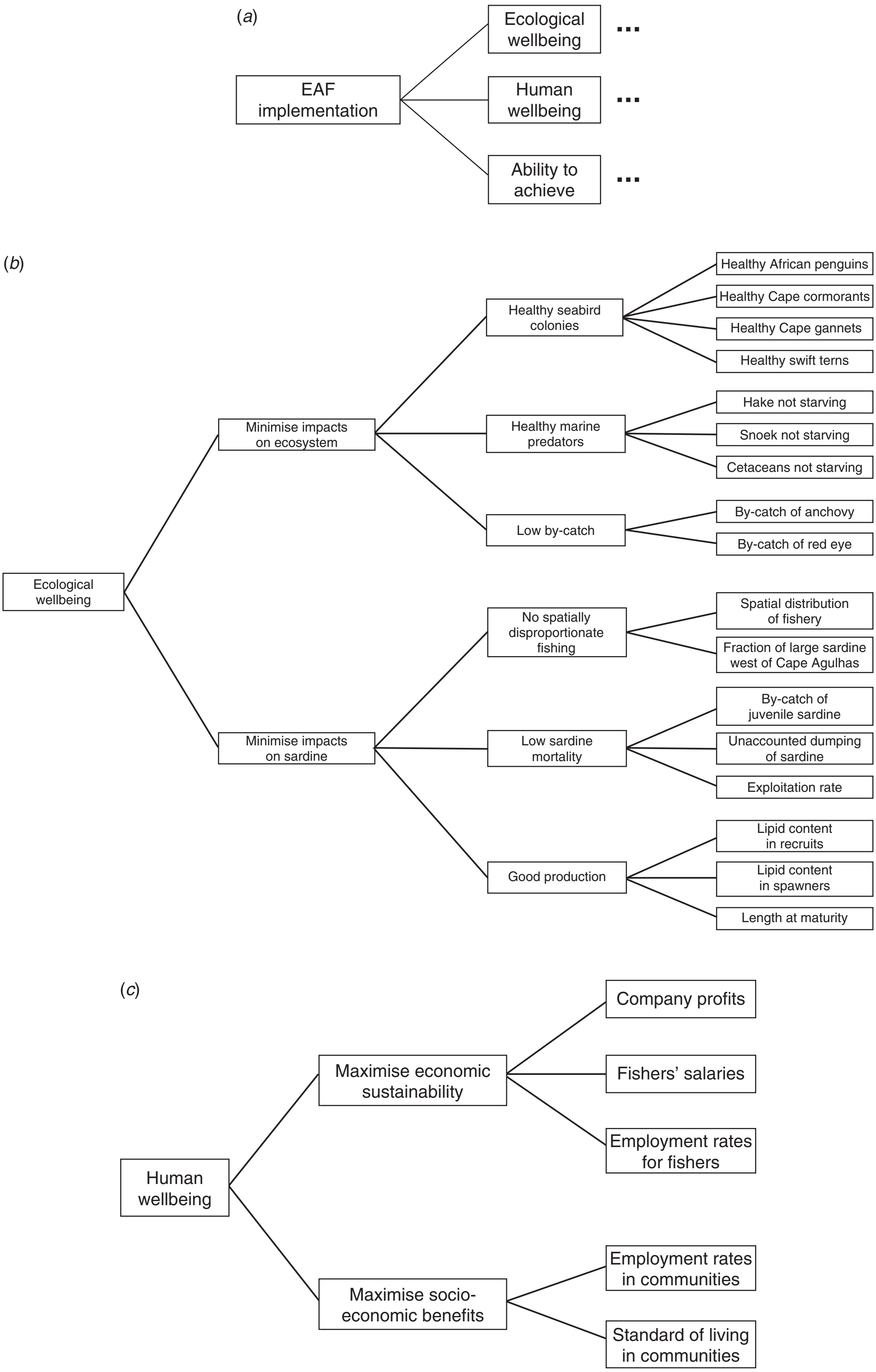

Fig. 2. The logic tree representing the key criteria based on which the fuzzy system evaluates the South African sardine fishery in terms of an Ecosystem Approach to Fisheries.

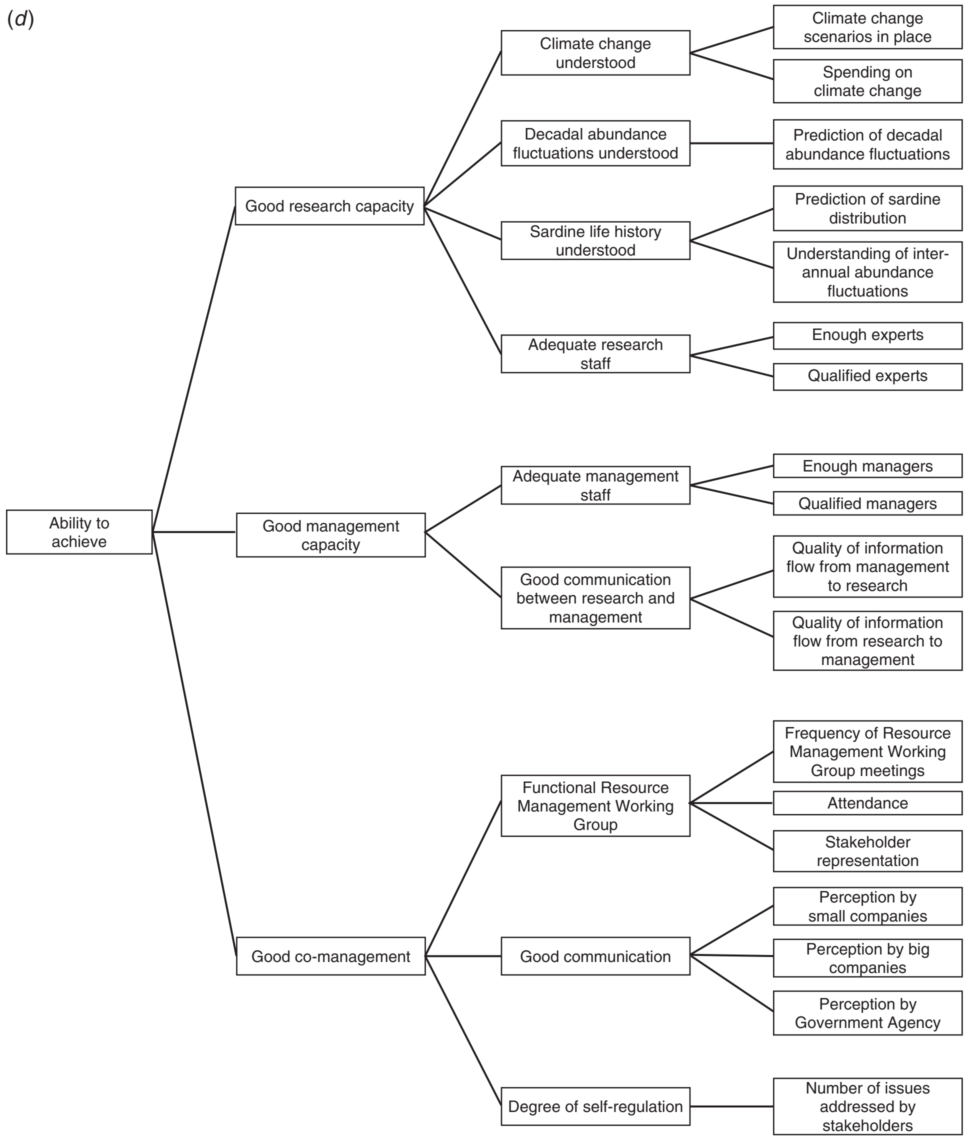

Fig. 2. (Continued)

of nodes in a network (Miller and Saunders 2002). Each layer can increase the number of fuzzy AND nodes, and thus the number of times a penalty is given.

The EAF monitoring tool is structured hierarchically, that is truth values generated on the input level are propagated upwards to influence the truth value of the next higher node. The overall EAF assessment is thus an aggregation of all input values. Consequently great care has to be taken in selecting appropriate input variables.

Results are visualised as bar charts with green bars describing degrees of trueness and red bars describing degrees of falseness.

Prototype development

The structure of the model follows the hierarchical tree approach using the three categories (human wellbeing, ecological wellbeing and ability to achieve EAF) that are recommended in the FAO guidelines for responsible fisheries (FAO 2003) and used in ERA (Fletcher *et al*. 2002; Fletcher 2005). Issues relevant for the South African small pelagic fishery were identified in Nel (2007). During a consultative process with key experts from research, management and industry, the main issues were structured into a hierarchy of objectives by breaking general top-level objectives into increasingly specific operational objectives (Fig. 2; Paterson 2007). This objectives hierarchy was then implemented in NetWeaver with dependency networks representing objectives and input variables representing the indicators for operational objectives.

Input variables include the IUCN status of selected seabirds, the condition of populations of marine top predators, by-catch in the pelagic fishery, sardine mortality, sardine production, socio-economic benefits returned by the fishery, management and research capacity in the responsible government agency, and co-management (Appendix 1). Of the 40 variables, 14 are based on data and 26 rely on expert opinion. The threshold

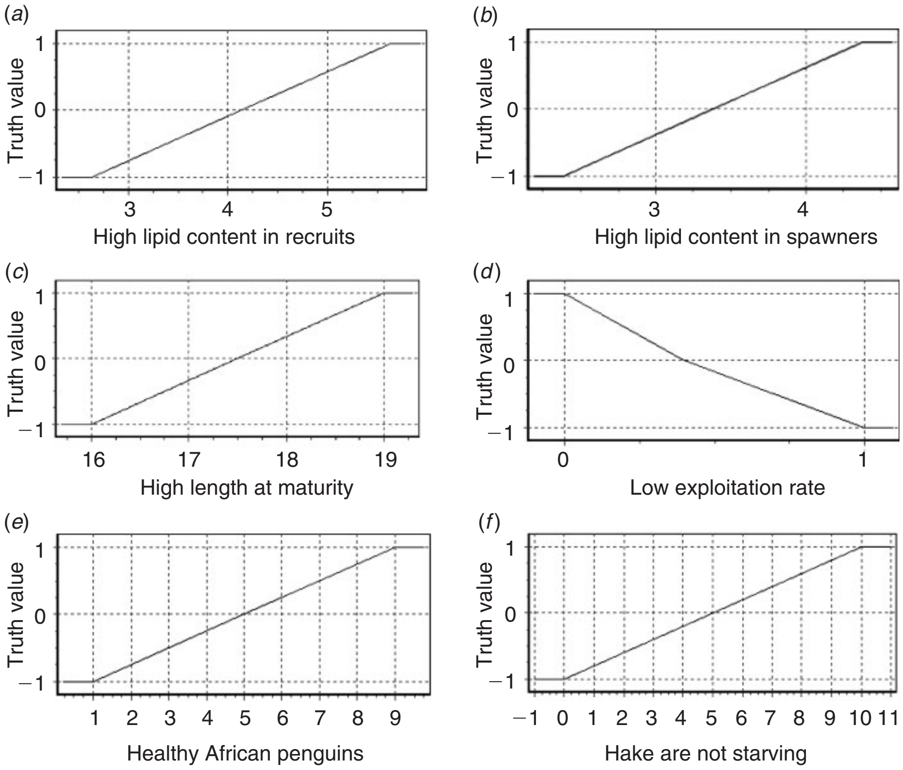

Fig. 3. Fuzzy arguments defining the truth value of some of the ecological variables: (*a*) high lipid content in recruits; (*b*) high lipid content in spawners; (*c*) high length at 50% maturity; (*d*) low exploitation rate; (*e*) healthy African penguins; and (*f*) hake are not starving.

parameters for variables based on data were provided by experts. All variables were given equal weights, following the NetWeaver recommendation (Miller and Saunders 2002).

Two input datasets for 1999 and 2005 were compiled, based on empirical data and expert opinion elicited from key experts. Expert opinion was elicited through unstructured interviews and small group discussions. Propositions were formulated for each parameter and experts were asked to rate the trueness of the proposition on an 11-point scale. If more than one expert was asked, the input value was based on group consensus. The outputs are expressed as truth values between -1 and $+1$, describing the trueness of the overall proposition 'EAF implementation is successful' as well as the trueness of the component propositions 'human wellbeing is high', 'ecological wellbeing is high' and 'ability to achieve EAF is high'.

Model evaluation and sensitivity analysis

The EAF monitoring tool was run with both the 1999 and 2005 data, and outputs were examined by experts for their concordance with general perception of the state of the ecosystem and management performance. We examined the robustness of the model to different input values by changing each input variable at a time across the entire input interval while holding all other variables constant. The impact of changing a single variable depends on the values of the remaining variables. We therefore did three test series, holding all unchanging variables at input values corresponding with truth values that were (1) 80% false, (2) 80% true, and (3) 'realistic', using input data for 1999. The input for each variable was incremented by a value close to or equivalent to a 20% positive truth value. For example, length at 50% maturity (100% false 19 cm, undetermined 17.5 cm, 100% true 16 cm) was incremented 10 times, each time by 0.3 cm. Variables defined over an input range of 0–10 were incremented by 1 and increments were repeated 10 times. Variables based on IUCN categories that were defined from 0 to 9 were incremented nine times.

As each layer in a NetWeaver model hierarchy can increase the number of times a penalty is given by the fuzzy AND node, it is possible that model structure can influence model results. If the number of levels does not impact the overall result a model can be structured interactively with stakeholders and the structure can reflect stakeholder preference and thus add transparency. If structure has an impact on the result this needs to be explicitly understood, and guidelines for structuring will be helpful. We created a copy of the network 'Ecological Wellbeing'. The hierarchy of this network was flattened by putting all ecological variables, which were originally structured into three levels, into one level. We then repeated the sensitivity test with both the hierarchical and flat networks. Results were compared with those from the previous sensitivity test. We assumed that if the hierarchy has no effect on the model output, the sensitivity results should be the same.

We chose an 11-point scale for opinion-based variables, assuming that high input resolution is necessary for model robustness. A large scale may, however, introduce expert bias as it is difficult to distinguish clearly and consistently between individual points on the scale. There may be a need to balance input resolution and input bias. We tested model sensitivity to input scales by repeating the sensitivity analysis, but converting the 11-point scale for variables based on expert opinion to a 5-point scale and a 3-point scale (Table 1).

Results

Based on realistic input data, the EAF monitoring tool evaluated the South African sardine fishery with respect to EAF for the years 1999 and 2005 respectively (Fig. 4). According to these results, ecological wellbeing decreased in that period, whereas the performance of the fishery with respect to institutional and social criteria has improved. Impacts of the fishery on the wider ecosystem have remained largely the same, that is close to undetermined, although the condition of marine predators was rated higher for 1999 than for 2005. Impacts of the fishery on its target stock have worsened due to an increase of spatially disproportionate fishing and decreased sardine production. Institutional improvements are mainly in terms of research and management staff and a perceived higher degree of self-regulation by stakeholders. The evaluation of the latter has changed from ~80% false to 40% true, whereas the functionality of the Resource Management Working Group, the main institutional mechanism for co-management, was rated false for both years and lower for 2005 than for 1999. Maximum economic sustainability and optimum socio-economic benefits were evaluated close to undetermined for 1999. For 2005, both were evaluated as ~50% true.

Table 1. Conversion from 11-point scale to 5- and 3-point scales

11 point	5 point	3 point	
0	0	0	100% false
1	0	0	80% false
2	1	0	60% false
3	1	0	40% false
4	2	1	20% false
5	2	1	Undetermined
6	2	1	20% true
7	3	2	40% true
8	3	2	60% true
9	4	2	80% true
10	4	2	100% true

During the first sensitivity test, we changed variables one at a time while holding all other variables at input values corresponding with a truth value of 80% false. The first increment (from a corresponding truth value of 100% false to 80% false) caused an average change of 0.198 in output truth value while all further increments showed no or negligible effect (Fig. 5*a*). Changing each variable, while holding all other variables at 80% true, caused changes in output after every increment step. The highest change occurred after the first increment and then decreased with each further increment (Fig. 5*b*). Once the increment step crosses the undetermined threshold value the changes in output are below 0.1. Holding all variables at realistic values while changing one variable at a time caused an initial change in truth value and further increments showed negligible effect (Fig. 5*c*).

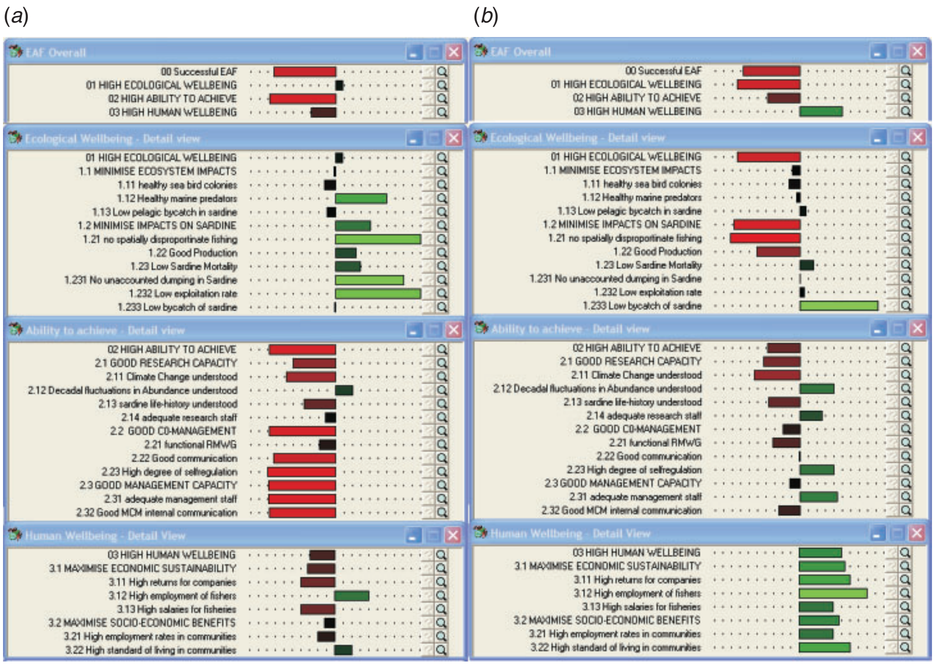

Fig. 4. EAF evaluation by the fuzzy system for (*a*) 1999 and (*b*) 2005. Red bars extending to the left indicate degrees of falseness, green bars extending to the right indicate degrees of trueness.

Comparing the sensitivity test results after reducing the scale of opinion-based variables from 11 points to 5 and 3 points does not increase sensitivity of the model for both the false and the true scenarios (Table 2). However, the 5-point scale shows a change after the first increment that is higher than the initial change of the 11-point scale, whereas the initial change caused by the 3-point scale is lower (Table 2). In the realistic scenario for both the 5-point and the 3-point scale the model returns 100% false for all test cycles (Table 2), because several inputs were transformed into truth values of 100% false.

Truth values of the flat network 'High Ecological Wellbeing' resemble the results for the original steeply-structured network (Fig. 6). Sensitivity is highest when remaining variables are false and lowest when remaining variables are true. The difference in truth values between the steep and flat networks are small for the realistic input scenario (Table 3) and highest for the true input scenario. In all input scenarios the truth values of the flat network are lower than those of the steep network (Fig. 6).

Discussion

Model evaluation

The results for 1999 and 2005 correspond with expert opinion on the status of the fishery in these years. In 1999, the abundance of pelagic fish had increased since the low levels in the 1980s and ecological wellbeing is assumed to have been good. Since then, sardine biomass increased until 2002, even after the onset of an eastward moving of the fish. The main reason the outputs for ecological wellbeing show small truth values for 2005 is the increase in spatially disproportionate fishing linked to this eastward shift. Another factor is the decrease in productivity, which corresponds with the decrease in sardine biomass since 2002.

Many of the input values used to evaluate the realistic scenarios for 1999 and 2005 are still somewhat unreliable. In particular, many of the variables describing institutional aspects rely on expert opinion rather than measurable indicators. However, although the lack of reliable input data is a constraint that has to be taken seriously, this does not lessen the value of this modelling exercise. The move from single-stock management towards EAF involves many, often conflicting, objectives and as such presents a complex problem scenario. Like any multi-criteria decision analysis (MCDA), the purpose of this decision-support tool is to structure the evaluation of EAF and to distil its complexity into key factors (Belton and Stewart 2002). The idea is not to find indicators that can be measured in order to increase the correctness of the system, but to find indicators that are accepted as relevant by stakeholders, generate insight and understanding and can be utilised in a transparent model reflecting the decision process.

The selection of indicators and the way these are interlinked within the model represent an important structuring process that reflects expert understanding of the problem at hand. This knowledge cannot be challenged by a purely statistical analysis. Many of the factors involved cannot be measured in precise, quantifiable terms. This does not mean, however, that these factors are unimportant or meaningless. The development of the EAF monitoring tool described here has been a process of identifying key factors, irrespective of whether they represent measurable criteria. Many of the variables that inform this decision-support tool will always be based on human values and subjective opinion. The strength of this approach lies in the fact that it allows the combination of objective measurement and value judgements. Naturally, value judgements are subjective. Subjectivity, however, is inherent in all decision making, the choice of criteria and the relative importance that is given to them. To improve decision making, therefore, does not mean to eliminate subjectivity but to render it explicit (Belton and Stewart 2002). Consequently the purpose of this tool is not so much measurement and precision

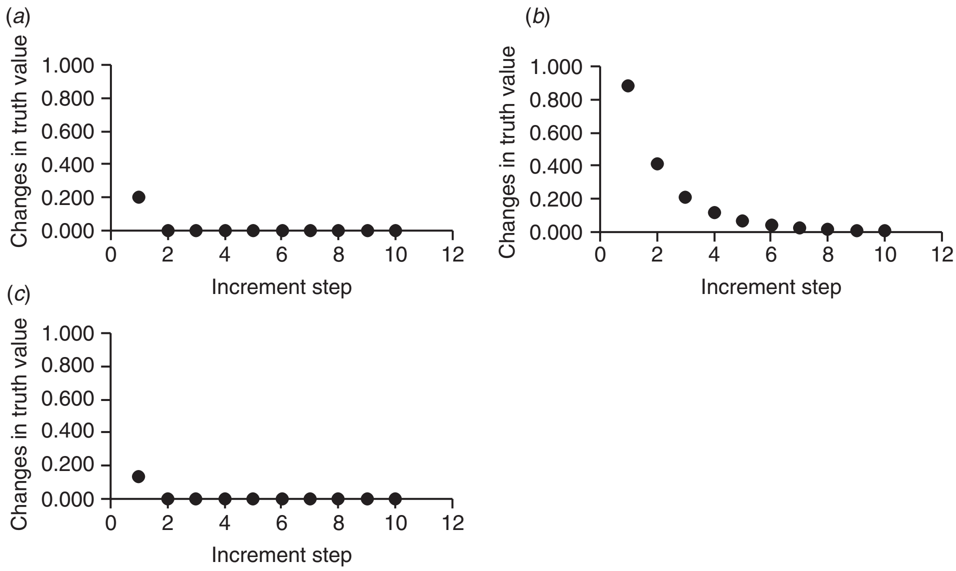

Fig. 5. Sensitivity of overall truth value of proposition 'EAF is successfully implemented' to changes in input while holding remaining variables at (*a*) 80% false, (*b*) 80% true and (*c*) realistic values elicited form experts. The dots are the average changes in truth value after each increment.

but synthesising many perspectives and enhancing understanding of all the factors involved and their relation to one another.

Sensitivity analysis

Recognising the inherent subjectivity of the variable selection, the present study is not concerned with evaluating the sensitivity of individual variables or the influence of their inclusion or omission on the overall result. We used sensitivity analysis to gain a better understanding of the workings of the model and to get a feel for its vulnerability to experts' misjudgement. Sensitivity results for the realistic input scenario show that the model is robust towards changes in input. However, sensitivity is reduced when the truth values of the remaining variables are small, and is greatest when truth values of the remaining variables are large and the value of the variable under investigation is small. Thus a negative truth value impacts more strongly than a positive truth value and system outputs are conservative. Because nodes throughout the model use the fuzzy AND, which is designed

Table 2. Sensitivity of the output truth value to changes in input and length of input scale

The numbers express the change in output truth values between increment steps

11-point input scale										
Remaining variables at 80% false										
Increment step	1	2	3	4	5	6	7	8	9	10
Minimum change in output (%)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum change in output (%)	25	0.2	0.0	0.0	0.1	0.1	0.0	0.1	0.0	0.0
Average change in output (%)	23	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Remaining variables at 80% true										
Increment step	1	2	3	4	5	6	7	8	9	10
Minimum change in output (%)	61	32	7.4	1.3	6.2	3.5	1.6	0.3	0.5	0.0
Maximum change in output (%)	9190	3936	2173	1236	727	445	273	173	82	36
Average change in output (%)	933	454	241	133	78	47	28	17	8.8	3.6
Remaining variables at realistic input values										
Increment step	1	2	3	4	5	6	7	8	9	10
Minimum change in output (%)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum change in output (%)	37	1.9	1.5	34	3.0	0.1	0.3	1.0	1.6	34
Average change in output (%)	32	1.1	0.6	1.8	0.2	0.1	0.0	0.1	0.1	1.8
5-point input scale										
Remaining variables at 60% and 80% false										
Increment step	1	2	3	4	5	6	7	8	9	10
Minimum change in output (%)	23	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum change in output (%)	30	0.5	0.1	0.1	0.1	0.1	0.1	0.3	0.1	0.0
Average change in output (%)	29	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Remaining variables at 60% and 80% true										
Increment step	1	2	3	4	5	6	7	8	9	10
Minimum change in output (%)	75	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum change in output (%)	1053	335	172	93	52	19	9.6	100	100	1.8
Average change in output (%)	286	76	30	11	4.7	1.8	0.9	4.9	5.0	0.2
Remaining variables at realistic input values										
Increment step	1	2	3	4	5	6	7	8	9	10
Minimum change in output (%)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum change in output (%)	19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Average change in output (%)	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3-point input scale										
Remaining variables at 50% and 80% false										
Increment step	1	2	3	4	5	6	7	8	9	10
Minimum change in output (%)	0.254	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum change in output (%)	0.258	0.016	0.007	0.005	0.003	0.001	0.001	0.000	0.001	0.001
Average change in output (%)	0.258	0.002	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000
Remaining variables at 50% and 80% true										
Increment step	1	2	3	4	5	6	7	8	9	10
Minimum change in output (%)	0.090	0.000	0.000	0.000	0.002	0.002	0.001	0.001	0.000	0.000
Maximum change in output (%)	0.581	0.289	0.026	0.016	0.008	0.006	0.007	0.007	0.006	0.007
Average change in output (%)	0.547	0.022	0.016	0.005	0.004	0.003	0.003	0.002	0.002	0.003
Remaining variables at realistic input values										
All outputs 100% false										

to produce conservative estimates, these results are in accordance with expectations from theory. What is surprising is that the flatter-structured network produces results that have smaller truth values than the steeply-structured one. We assumed that a steep, multi-layered structure with several fuzzy AND nodes would produce reduced truth values due to repeated penalties by the fuzzy AND. Results indicate, however, that the opposite is the case. We examined an input scenario where one variable is 80% false and all others are 80% true (Fig. 7). In the flat structure all antecedents are on the same level, which means that the false value has great pulling strength against all other truth values. In the multi-layered hierarchy the false value has great pulling strength in the lowest level network, resulting in a negative truth value. This result is then combined with the positive truth values of the other networks to produce a result less negative, which is again combined with positive levels on the next level. These test results show that the structure of NetWeaver knowledge bases is not arbitrary but meaningful. Structuring networks into multi-level hierarchies impacts on the overall truth value. Therefore, great care has to be taken when designing a knowledge base. This result is valuable for knowledge-base developers. Although NetWeaver knowledge bases are transparent, the real workings of the fuzzy AND and its impact within knowledge-base structure are not immediately apparent.

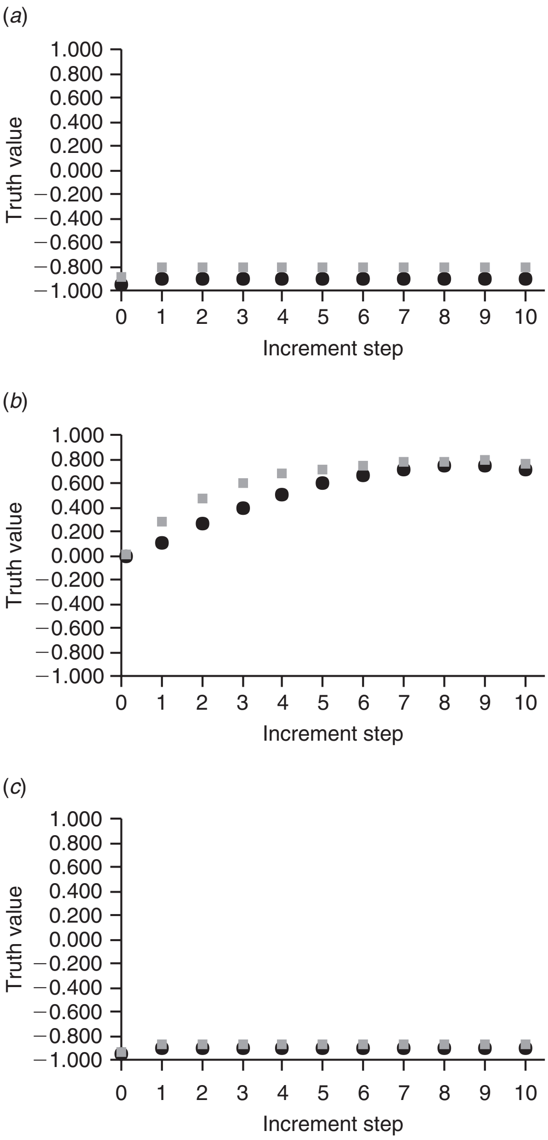

Fig. 6. Average output values for network 'High Ecological Wellbeing'. Input values for one variable at a time were incremented across the entire input range while first holding remaining variables (*a*) true, then (*b*) false and then at (*c*) realistic input values elicited form experts and data. The grey squares are the average truth values of the steeply structured network, the black dots are the average truth values of the flat network.

Although the shortening of the input scale to five and three points does not impact on model sensitivity for the false and true scenarios, the results for the realistic scenario indicate that these scales are too coarse. Jarre *et al.* (in press) found that reducing the fuzzy-output values from a continuous scale between −1 and +1 to four categories (critical, bad, medium, good) generated useful results. The reduction of the input scale, however, means that many input values, which on the 11-point scale were various degrees of false, are now 100% false. As a consequence, most networks return 100% false and the overall model result is 100% false, too. This indicates that these short input scales are not appropriate in a fuzzy model, despite the difficulty for experts to give meaning to the individual points on the scale. Further research is needed to find the ideal balance between length of input scale and expert ability to use it. Burgman (2005) lists several approaches to eliciting expert knowledge. Among these is the use of Kent scales to express degrees of probability. This approach can be used to link linguistic terms to truth values and rank them according to degrees of trueness (Table 4). Full descriptors for each point on the scale will go a long way in reducing expert bias.

Application of the tool in fisheries management

South Africa committed to EAF implementation at WSSD and has a dedicated EAF scientific working group, which has coordinated the South African portion of the Benguela Current Large Marine Ecosystem feasibility study investigating how to move towards implementing EAF within the region (Shannon *et al.* 2004; Nel 2007). Given that fisheries management is largely undertaken on a single-species basis worldwide, a shift towards

Table 3. Difference (%) in truth values between steep and flat structure of network 'High Ecological Wellbeing'

Increment step	0	1	2	3	4	5	6	7	8	9	10
Remaining variables false	0.1	0.1	0.2	0.2	0.3	0.3	0.4	0.4	0.5	0.4	0.4
Remaining variables true	9.2	37	44	42	35	27	20	15	12	11	11
Remaining variables at realistic values	1.4	2.4	2.5	2.5	2.6	2.6	2.6	2.6	2.6	2.4	2.4

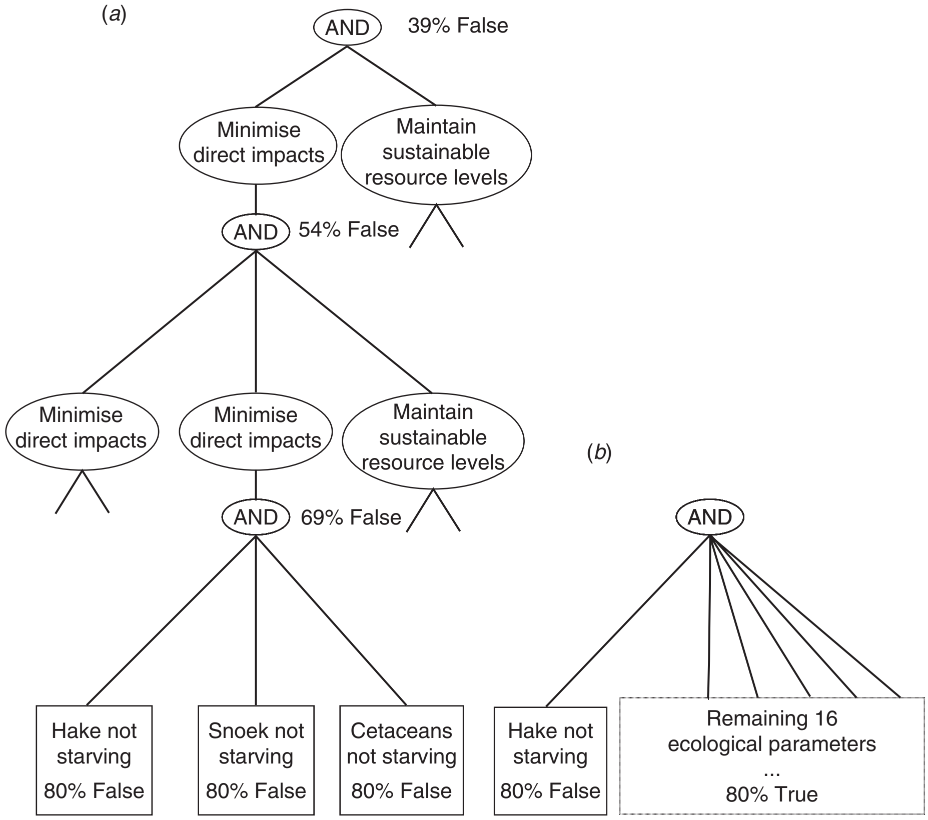

Fig. 7. Propagation of truth values for network 'High Ecological Wellbeing' based on 17 input variables. Square boxes symbolise input variables, ellipses symbolise sub networks. The 17 ecological variables were first structured into a (*a*) multi-level hierarchy then (*b*) flattened into a single level.

Table 4. Possible Kent scale to relate linguistic terms to degrees of trueness

Expression	Score	Truth value
Absolutely true	9	100% true
Almost completely true	8	75% true
Half true	7	50% true
Slightly true	6	25% true
Neutral	5	Undetermined
Slightly false	4	25% false
Half false	3	50% false
Almost completely false	2	75% false
Absolutely false	1	100% false

EAF will require an adaptive management framework, which will rely on rapid monitoring and assessment methods (FAO 2003; Degnbol and Jarre 2004). Such methods depend on good data collection based on key indicators that have been agreed upon by stakeholders (Fairweather *et al*. 2006*a*). The fuzzy-logic knowledge-based system presented here provides a tool to monitor and evaluate the performance, in the ecosystem context, of the South African pelagic fishery, directed at sardine. Such an evaluation requires that many different aspects are taken into account, such as the impacts of the fishery on the target resource, as well as impacts on the wider ecosystem. Ecosystem impact is not only at the level of marine predators or competing species, but also includes the human dimension of the fishery, that is the resource users and the managers of the resource base. The knowledge-based system provides a structured representation of the key indicators that determine the successful implementation of EAF in the sardine fishery. The model integrates indicators for all three dimensions of EAF and includes not only those indicators for which data are currently available but also specifies knowledge needs. A monitoring system such as this is necessary to keep track of the status of the stock within an ecosystem, the status of the ecosystem itself, and to pick up signals that indicate negative trends that require management intervention.

Fisheries evaluation in terms of ecosystem performance based on indicators has been undertaken in Western Australia (Fletcher and Head 2006). We have extended this approach in the Benguela region. In an attempt to provide a means of gauging progress towards implementing an EAF in the Benguela region, Nel *et al*. (2007) synthesised the eight ecological risk assessments undertaken in South Africa and Namibia into a generic checklist of broad operational objectives with corresponding management indicators. The present study complements this in further detail by integrating the performance indicators identified in the risk assessment analysis into a coherent framework where the influence of alternative indicator values can be explored to assess their influence on the overall result, that is the overall assessment of the performance of the particular fishery under consideration with respect to the ecosystem approach to fisheries. The model allows inter-annual comparison, which can provide useful insights by showing how indicator values influence the fulfilment of objectives and thus the evaluation of the fishery. Moreover, it is possible to test existing assumptions. For example, once the best possible representation of the factors involved has been found, input scenarios for the 1980s, when the sardine fishery was very depressed, could be compiled based on available data and expert opinion. This exercise may help to test the assumption that a shift towards EAF is beneficial for the resource, the ecosystem and society, despite the many trade-offs that are likely to be required to balance the often contrasting objectives of ecological wellbeing, human wellbeing and good governance.

Multi-criteria decision making

Integrating the many different and diverse aspects of EAF is a complex task that involves balancing multiple objectives and values. Although the usefulness of Multi-Criteria Decision Analysis (MCDA) techniques to fisheries management has been demonstrated (e.g. Stewart 1988; McDaniels 1995; Mardle *et al*. 2000), the methodology is not widely used in this field (Mardle and Pascoe 1999; de Steiguer *et al*. 2003; Kiker *et al*. 2005; Leung 2006; Linkov *et al*. 2006). A study similar to ours, evaluating a fishery's performance based on multiple criteria, has been undertaken for the shrimp fishery in Trinidad and Tobago (Soma 2003) using the MCDA technique of the Analytical Hierarchy Process (AHP). AHP has been used to balance key management objectives for the English Channel fisheries based on stakeholder preference (Mardle *et al*. 2004).

MCDA is a collection of formal approaches that seek to take explicit account of multiple criteria in helping individuals or groups explore decisions that matter (Belton and Stewart 2002). Knowledge-based systems represent one such approach. The close links between knowledge-based systems and classical MCDA systems have been described (e.g. Finlay 1994). Often, knowledge-based systems are implemented using decision rules (e.g. Goodwin and Wright 2004), but the approach we use here, and which is implemented in NetWeaver, is somewhat closer to methods of classical MCDA.

The problem of the routine evaluation of the ecosystem performance of a fishery involves considerable uncertainty (*sensu* Belton and Stewart 2002). Multi-attribute theory (MAUT) is a classical MCDA technique used in this situation, which has a sound theoretical foundation. In MAUT, the preferences for each criterion are projected onto a scale from 0 to 1 called utility function. This function reflects not only the ordering of the preferences, but also models the decision-makers' attitude to risk. Typically, the utility functions are derived by an analyst requesting preferences in a series of hypothetical lotteries from the decision-makers. An aggregation function then combines preferences across criteria, allowing inter-criteria comparisons, and therefore the assessment of tradeoffs. The aggregation function can be an additive function of the weighted utility values (e.g. Goodwin and Wright 2004) or a multiplicative function of these (e.g. Belton and Stewart 2003).

Because of its complexity, the process of eliciting the utility functions for the individual criteria can be tedious and, particularly if the decision-makers are unfamiliar with the mathematical probability theory, potentially misleading (Belton and Stewart 2002; Goodwin and Wright 2004). Fuzzy-set theory (Zadeh 1965, 1995, 2006) can be used to deal with the potential pitfalls. Some advantages in practical application of fuzzy-set theory in multi-criteria decision making have been acknowledged even by critics (e.g. Kickert 1978). In this case, the utility functions are replaced by fuzzy-membership functions (e.g. Zimmermann 1987; Matthieu-Nicot 1994). The fuzzy-membership functions as implemented in NetWeaver do not allow for curvilinearity, but curves can be approximated by explicitly defining the undetermined point, which is then connected to the fully true and fully false points with two straight lines, respectively. With respect to aggregation functions, the NetWeaver fuzzy AND is a special case of a range of available fuzzy-set theoretical operators (e.g Zimmermann 1991) that soften the constraints of the strict logical meaning of 'and' and 'or'.

Other possibilities of dealing with risk and uncertainty have been proposed (Stewart 2005), emphasising an overriding need in any MCDA approach, for the model to be fully understandable to all participants in the process. This is a potential weakness of fuzzy-set theory, but on the other hand, successful applications are documented (see Introduction). In assembling this first prototype, we placed our emphasis on achieving broad participation rather than on fine-tuning the decision model.

The advantages and disadvantages of different MCDA techniques have been reviewed (Belton and Stewart 2002; Linkov *et al*. 2006). With respect to fisheries applications, Jarre *et al.* (in press) highlight that it is often appropriate to apply more than one technique to a given problem. In this case the choice of the technique may ultimately depend on stakeholder preference. Placing a problem structure such as the one presented here into an expert system-shell links the decision process to the underlying database and allows exploration of alternative values without having to leave the coherent and transparent framework.

Conclusion

The present study describes a prototype decision-support system. Although the usefulness of the method to address the ecosystem performance of a fishery has been demonstrated, the prototype requires further refinement in continued collaboration with stakeholders. In parallel, research is being carried out in the southern Benguela region to refine the underlying indicators (e.g. Fairweather *et al*. 2006*a*, 2006*b*) as well as the database (e.g. Shannon *et al*. 2006). At the outset of the present study the complexity and the multidisciplinary challenge appeared overwhelming. However, the present study confirmed that problem structuring is an important part of the decision-making process (Belton and Stewart 2002). Representing the complex problem in a coherent structure helped stakeholders to understand their particular role in solving the problem at hand and facilitated knowledge elicitation from experts. Breaking the high-level goals (e.g. high human wellbeing) into operational objectives (e.g. high employment in coastal communities) and indicators (e.g. fraction of casual employment) improved our understanding of the breadth of the issues. At the same time, the structure ties the various issues into a coherent context and helps to communicate the management problem among stakeholders. A particular strength of the approach is that it facilitates the use of both quantitative and qualitative indicators in a single framework for management purposes, thereby enabling both ecological and socio-economic inputs and criteria to be considered simultaneously – exactly what is envisaged and what is needed for an EAF.

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