

Substituting model based indicators in Harvest Control Rules by observations using fuzzy logic methodology

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Abstract

Harvest Control Rules are predefined heuristic decision rules to provide quota advices for managed fisheries. Frequently statistical methods and biological assumptions expressed in mathematical models, are used to provide the Harvest Control Rules with initial information (indicators values). The aim of this paper is to investigate a possible way forward of replacing these inputs by quantities of measurable observations, e.g. catch-at-age statistics. The paper presents a method by which recruitment indexes and stock biomass indicators are obtained by non-parametric use of annual catch-at-age records, without filtering the raw data (observations) through mathematical models. Two related methods, applied on three empirical cases, are provided: First, showing that recruitment strengths of the Northeast Arctic cod, haddock and saithe stocks, obtained by fuzzy logic methodology, are satisfactory captures by the use of catch-at-age data. Secondly, stock size indicators are estimated for the three species by the same catch-at-age data. The second task turns out to be more challenging than the first, but also in the case of stock size evaluation, the suggested procedure provides reasonable results when compared to standard stock assessment methods.

Keywords: Stock assessment; Fuzzy logic; Northeast Arctic fisheries;
and Harvest Control Rules

Introduction

Following the principles of the 1992 UN Rio Declaration, FAO in 1996 issued guidelines on precautionary approach to fisheries and species introduction (Anon., 1996; Kvamsdal *et al.*, 2016). In 2000 the Convention on Biological Diversity led to the identification of Ecosystem Approach as an overall strategy for the management of natural resources. Anon. (2006) provides a detailed description on how to implement the principles in fisheries within the area of the International Council for the Exploration of the Sea (ICES). A large number of fishing nations and fishery management institutions have adopted the guidelines (Punt, 2006) and Harvest Control Rules (HCRs) have become a methodology of precautionary management in many fisheries.

Up to recently there has been a widespread belief among fishery management institutions that all knowledge necessary for sound management of fisheries could be embedded in biological models, capturing the dynamics of biological systems as well as its interactions with fishing activities. Management failures, and the broader ecosystem perspective, have created scepticism towards the use of mathematical modelling in fisheries management. Schnute and Richards (2001) ask managers to be sceptical, to expand their knowledge base, and to apply common sense when using models. In the development of fisheries management we may have arrived at a point where it is fair to ask: Is it possible to obtain sufficient scientific insight to build ecosystem models suitable for management? What will it cost, and can it be done in a transparent way? Reduced faith in the modelling approach, combined with the expenses associated with feeding increasingly data demanding models (Degnbol, 2001), call for new approaches to management and more efficient use of existing system knowledge, which not necessarily could be implemented in the model formulations. Increasingly complex and data demanding models lead to reduced transparency, reduced legitimacy, and reduced belief in the modelling approach to management (Dankel *et al.*, 2016; Kelly and Codling, 2006).

Stock assessment methods based on mathematical modelling and statistical techniques have undoubtedly been crucial for today's level of understanding of fisheries dynamics and for the successful management of many fisheries. This achievement makes it is also easier to express and utilise heuristic HCR procedures in fisheries management. It is fair to say that HCRs have been introduced as a continuation of previous management procedures based on mathematical models. This may also turn out to be a problem for a further utilisation of the capacities of a fully developed heuristic expert system (Clancey, 1983) for fisheries management.

Today HCRs are successfully introduced in a large number of fisheries (Kvamsdal *et al.*, 2016). In principle HCRs should not limited to only include biological measures (Garcia *et al.*, 2009). Rule based procedures open for the use non-biological indicators (such as social and economic measures), possibilities that so far are poorly explored and

hardly utilised. Heuristic decision rules (expert systems) allow vague knowledge and unspecified uncertainties to be integrated in the formulation of rules. Hypotheses and/or vague knowledge believed to be important (from biological, economic or societal points of view), can be added to existing sets of rules by reformulating existing rules or adding new. Reservation levels and intervals between 'go' and 'no' zones may include uncertainty and vagueness in the evaluation of tolerance levels. Together it constitutes the precautionary evaluation of possible short and long term consequences different levels of fish harvest may have on other parts of the ecosystem, the economy, and the society as a whole.

Heuristic decision rules organised in sets of HCRs, are used to evaluate the state of fisheries. The goal of the evaluation is not to identify stock size or fishing pressure but to estimate membership degrees in fuzzy sets, such as for example in the sets of *healthy stocks* and *overexploited stocks* illustrated by Figure 1. Being a fuzzy logic expert system, HCRs use membership functions, as those indicated in the figure, to identify the sets of highest membership degrees. This information is then used to decide the corresponding advice on TAC (Total Allowable Catch), all based on pre-defined rules. Crisp value estimations of stock size or other stock properties are merely means by which the selection of dominating fuzzy sets can be made.

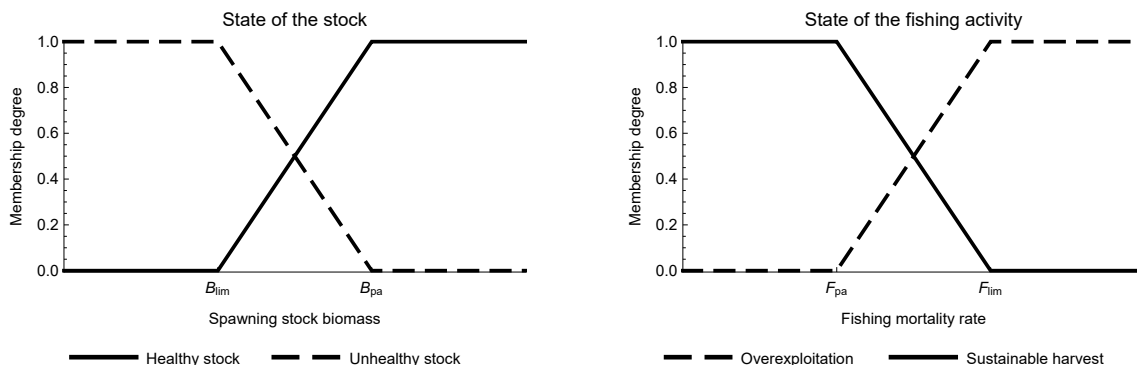


Figure 1: Standard membership functions used in the simplest versions of Harvest Control Rules. Membership degrees in four fuzzy sets are determined by the value of two indicators, which are measured along the two horizontal axes. B_{lim} is the limit value of spawning biomass below which the stock is 100% unhealthy, while the stock is 100% healthy above the precautionary level at B_{pa} . The corresponding values to the right is the critically high fishing mortality rate F_{lim} above which 100% overfishing occurs, while a 100% sustainable fishery takes place at and below the precautionary value F_{pa} .

Up to now HCRs in fisheries management have been implemented as an extension of previous management models. Indicators have been built on previous reference points and identified within the modelling framework developed prior to the HCRs. The rules commonly use model estimates of spawning biomasses and fishing mortality rates as indicators (inputs to the HCRs), as indicated in Figure 1. Hence, the transition from a model based to a rule based control system has been made possible, but is not yet completed. Since model outputs are not the goal, but rather a mean in the management

procedure, it is fair to ask: Could the parametric modelling part of the procedure be substituted by more direct use of basic observations and expert knowledge?

There are several reasons why the use of modelled indicator values in HCRs is problematic. Inclusion of model uncertainty (Dankel *et al.*, 2016) and lack of transparency (Kelly and Codling, 2006) are often mentioned as the most serious problems. There is also a tautological problem of model based inputs when targets and limits (illustrated by *pa*- and *lim*-levels in Figure 1) are identified by using similar assumptions as those embedded in the model. The example in Figure 1 shows how estimated values of spawning stock biomass and fishing mortality rate – commonly used as indicators in HCRs – link to membership degrees of different fuzzy sets. Indicator values are often interrelated; estimated within the same modelling framework and sharing observation and modelling uncertainties.

Feigenbaum (1977) sets up a road map for heuristic rule-based case studies where the central organising principle is what he refers to as the *Line-of-reasoning*, which should be possible to explain in a language convenient to the user. Feigenbaum claims this to be necessary for the right use of an expert system (which in his terminology is called *knowledge engineering*), and for system development (debugging and extending the knowledge base). It may be questioned if a comprehensible *Line-of-reasoning* today exists for the users of management advices.

The aim of this paper is to investigate a possible approach of omitting the use of parametric models without losing important information hidden in data set structures; information which today is filtered through model assumptions and non-transparent tuning procedures. The Virtual Population Analysis (VPA; see Gulland, 1965) is an example of a fairly transparent accounting system based on consistency and fixed natural mortality rates. The less transparent eXtended Survivor Analysis (XSA) with improved tuning procedures, employing information from other data sources, clearly provides more reliable estimates of recent stock history (Shepherd, 1999). For the case studies provided in this paper – the Northeast Arctic (NEA) cod, haddock and saithe fisheries – existing XSA estimates are compared with results from suggested alternative methods, acknowledging XSA as a model within the class of well functioning integrated statistical year class models.

Data and method

A simple method on how to utilise fuzzy set theory on catch-at-age data for the evaluation of year class (or recruitment) strength in age structured fish populations is presented below, providing examples from the NEA cod, haddock and saithe stocks. The methodology builds to some extent on the ideas of Sakuramoto (1995) and Mackinson *et al.* (1999), also referred to in Eide (2016) where a number of management performance indicators

are suggested. Sakuramoto (1995) and Mackinson *et al.* (1999) show how catch-at-age data can be used to estimate recruitment strength by the use of fuzzy logic techniques.

Table 1: Registered catch quantities in thousand tons distributed on year classes (year of birth) and age of capture (from 3 to 13 and above), from tables 3.6 and 3.8 in Anon. (2016).

Year class	3	4	5	6	7	8	9	10	11	12	13+
1943	1.403	7.388	39.128	166.825	147.686	116.509	123.297	66.906	52.590	21.125	18.946
1944	0.227	2.052	39.088	76.896	95.339	76.285	53.429	57.760	29.808	13.819	8.690
1945	0.048	4.561	37.468	88.110	130.387	62.730	63.671	66.746	31.616	11.285	5.036
1946	0.367	7.011	88.978	141.748	63.905	46.387	67.194	54.345	26.632	10.251	5.961
1947	0.500	64.677	150.560	107.115	123.124	119.977	83.178	46.705	28.516	8.604	7.788
1948	9.875	96.563	143.411	198.479	231.085	217.137	97.431	76.991	26.873	15.297	15.511
1949	10.604	81.821	184.458	279.111	250.806	167.832	74.826	61.071	35.086	16.147	9.858
1950	18.965	119.482	228.072	458.364	251.525	150.659	125.993	99.121	48.261	17.392	9.988
1951	5.048	21.462	138.889	128.678	112.837	76.615	44.309	55.241	24.130	11.593	10.080
1952	1.249	14.020	27.726	78.215	66.408	41.049	35.615	21.006	9.822	1.748	4.624
1953	3.503	20.019	67.498	143.326	78.135	88.791	52.112	30.722	7.313	1.463	2.207
1954	5.716	69.460	217.979	143.615	125.130	110.640	76.597	28.673	9.834	4.296	3.859
1955	10.614	56.118	70.002	112.567	85.740	80.456	39.716	11.061	3.279	3.346	3.564
1956	11.308	49.911	129.631	152.082	107.975	45.535	20.450	10.869	6.204	1.179	2.700
1957	12.880	72.960	155.534	165.212	63.837	29.702	27.213	16.559	5.920	4.434	2.533
1958	14.098	93.811	197.327	108.950	61.320	70.670	55.369	24.319	15.935	2.857	2.797
1959	13.573	65.260	93.052	102.081	91.436	87.484	61.116	32.742	11.051	4.527	6.507
1960	4.223	25.252	80.648	75.719	73.889	69.040	67.584	24.692	6.568	4.268	2.711
1961	1.748	17.679	40.918	45.004	83.841	102.828	49.935	17.354	11.567	2.266	3.919
1962	5.976	41.177	93.467	226.948	230.153	132.468	70.260	34.839	7.136	3.674	3.710
1963	24.612	129.639	396.582	367.915	289.260	219.453	130.096	37.657	20.887	6.791	2.952
1964	9.995	122.210	293.369	275.658	182.020	152.796	125.684	44.071	19.126	5.242	3.664
1965	1.224	19.391	34.589	20.578	25.575	38.392	13.927	13.637	5.736	2.954	11.163
1966	1.015	9.821	16.327	25.629	23.846	19.184	15.022	8.705	6.057	4.839	2.036
1967	2.651	12.090	38.370	46.486	40.542	40.873	23.820	13.126	9.267	1.122	0.838
1968	3.489	34.982	93.940	104.353	87.090	58.920	36.557	9.791	3.937	0.733	0.571
1969	13.504	119.659	238.413	225.277	132.127	106.421	61.528	15.369	5.994	1.174	0.519
1970	111.820	288.669	251.577	237.654	204.009	141.922	72.209	23.203	9.543	2.803	1.413
1971	29.394	38.271	95.192	108.496	77.237	35.495	20.487	12.009	3.317	1.199	0.594
1972	18.566	83.469	194.959	122.169	52.967	31.256	28.034	6.025	2.645	1.311	0.995
1973	29.868	151.748	128.318	68.358	53.345	48.175	18.592	6.001	1.886	0.510	0.916
1974	19.401	36.774	54.159	68.905	64.928	35.595	19.775	5.794	1.617	1.457	1.338
1975	38.623	54.239	83.626	132.575	124.513	102.276	36.048	7.534	5.464	3.114	1.036
1976	3.010	9.568	29.956	55.887	67.846	40.689	11.927	5.583	2.276	0.972	0.461
1977	1.056	9.277	26.116	50.496	59.217	22.632	6.666	4.368	1.204	0.149	0.151
1978	1.669	13.816	42.789	63.070	52.638	23.728	7.826	4.936	0.454	0.253	0.067
1979	3.311	26.844	46.829	62.526	52.582	22.887	9.962	2.645	0.782	0.199	0.186
1980	2.611	27.483	56.168	70.350	47.152	17.676	6.219	1.761	0.566	0.946	1.219
1981	9.858	62.704	147.903	143.078	73.973	25.525	6.044	3.775	2.672	3.811	1.725
1982	23.156	90.161	152.226	121.809	81.612	31.871	23.639	19.650	13.957	9.433	3.252
1983	18.540	120.653	178.658	156.972	97.223	118.659	112.491	90.544	60.299	17.702	9.807
1984	6.688	19.358	42.136	39.576	73.046	70.278	42.514	27.789	10.261	2.392	4.259
1985	5.307	16.620	21.318	58.788	78.359	52.253	41.908	13.886	4.287	2.358	1.699
1986	3.763	9.212	35.404	72.515	60.505	52.099	18.777	7.477	3.212	1.038	1.011
1987	1.548	15.853	60.762	93.808	104.338	36.597	13.635	8.897	2.029	0.555	0.448
1988	5.211	56.544	137.328	172.724	122.057	60.317	33.441	8.975	1.966	0.886	0.566
1989	25.329	70.197	211.249	255.076	208.534	147.638	45.225	12.363	2.574	0.891	0.372
1990	8.176	77.277	205.286	247.252	224.927	128.080	52.968	12.385	3.087	0.984	0.693
1991	5.355	51.104	129.945	184.298	113.893	68.001	27.382	8.769	2.038	1.160	0.897
1992	3.757	31.948	106.538	93.134	50.647	29.913	10.709	4.052	1.521	1.527	0.750
1993	6.047	37.951	79.335	72.865	42.321	25.171	11.166	4.034	2.711	1.150	2.294
1994	8.594	93.318	142.937	110.471	80.007	55.099	18.361	13.933	5.463	1.802	1.229
1995	21.683	78.491	149.801	156.765	148.269	70.570	41.864	19.230	5.675	2.898	1.107
1996	4.726	34.418	100.665	156.285	131.407	85.517	39.156	12.123	4.515	2.317	1.406
1997	2.680	36.770	118.833	177.773	166.240	91.255	39.630	11.158	6.006	8.439	3.107
1998	3.329	35.067	117.938	166.091	145.973	71.128	26.846	13.904	7.560	8.354	5.914
1999	1.691	23.391	81.830	136.280	105.476	56.650	34.229	15.676	25.880	6.432	5.844
2000	4.866	43.195	177.636	186.779	131.377	105.861	57.356	31.659	27.741	13.050	9.104
2001	1.505	21.349	53.800	66.021	53.200	45.031	29.900	37.783	19.934	7.828	8.582
2002	4.012	54.760	115.065	98.903	80.246	85.992	72.355	42.963	26.904	11.515	10.392
2003	6.155	53.019	76.027	112.866	125.110	97.556	77.407	66.835	32.226	22.439	
2004	18.850	65.664	146.157	185.081	236.400	212.586	262.952	158.711	117.961		
2005	6.513	45.292	93.708	168.123	218.444	314.183	260.995	162.541			
2006	3.650	19.432	55.852	94.470	172.997	236.219	132.446				
2007	1.387	10.523	28.798	49.607	98.075	100.484					
2008	1.106	11.927	37.996	85.721	105.959						
2009	1.806	15.981	66.444	111.636							
2010	2.061	23.071	63.831								
2011	4.135	34.207									
2012	3.366										

Fuzzy set theory was first introduced by Lotfi Zadeh in the 1960ies (Zadeh, 1983 and 2002) and soon proved to be a practical tool with a wide area of applications, also related to fisheries management (Sakuramoto, 1995; Silvert, 1997; Mackinson *et al.*, 1999). The theory extends traditional set theory by introducing the concept of degrees of set

memberships. A fish stock could for example have partial membership in both the set of large stocks and the set of small fish stocks at the same time. Furthermore, it may be partial member in the set of overexploited stocks and the set of well-managed stocks at the same time (which in the HCR context could be when being between precautionary and limit values of a given indicator, see Figure 1). The principle provides a method to include characteristics that gradually change (e.g. age, size, etc.) or genuine vagueness in set theoretic studies. It is easy to link this to real world problems as for example to the management of fisheries. Obviously, there is no crisp value identifying the point at which a stock becomes for example overexploited. Similarly, a single fish – or a person – could have partial membership both in the set of young individuals and in the set of old individuals. As observers, however, we do not need to know the age of a person to have an opinion of in which of the two sets (of young and old individuals) the person has the highest membership degree. The phenomena is known from ancient time as *the Sorites paradox*. It refers to real vagueness of terms often involved in human evaluations and decisions. Fuzzy set theory aims to operationalise how to make decisions within this framework.

Table 2: Sixth part quantiles of each data set of catches-at-age from 1946 to 2015, illustrated graphically as curves in Figure 2

Quantiles	Age groups										
	3	4	5	6	7	8	9	10	11	12	13+
5/6	18.566	83.469	178.660	185.080	173.000	132.470	77.407	55.241	26.904	11.285	8.582
4/6	8.594	56.118	137.330	152.080	124.510	97.556	57.356	28.673	11.567	4.839	3.859
3/6	4.866	36.774	93.467	112.570	95.339	70.570	39.716	15.676	6.204	2.898	2.533
2/6	3.329	21.462	63.831	93.134	73.973	48.175	27.382	11.158	4.287	1.463	1.219
1/6	1.505	13.816	39.088	66.021	53.345	31.871	15.022	6.025	2.276	0.984	0.594

Table 1 shows the NEA cod catch-at-age data for the year classes from 1943 to 2012, available from the ICES Arctic Fisheries Working Group (AFWG) (Anon., 2016). The tabled data is presented as a Box-Whisker-plot in Figure 2 where the range of each box is defined by the 25% and 75% quantiles of catches-at-age over the covered period. These quantiles split, together with the 50% quantile (the median value), each data set into four fractions. For the purpose of this study we prefer to split each catch-at-age data set into six fractions, obtained by employing the five 1/6 quantiles (within the ranges of 16.7%, 33.3%, 50%, 66.7%, and 83.3% of the total catches-at-age).

Table 2 shows the 1/6 quantile values within the catches of each age group. The curves in Figure 2 connect the 1/6 quantile of each data set, serving as a measure of classifying each year class by catch-at-age data in sets of *very weak*, *weak*, *medium*, *strong* and *very strong* year class catches. For example, catches of age group 5 less than 39.088 thousand tons (which is the 1/6 quantile of age 5 years, see Table 2) is assumed to reflect a *very weak year class*, while catches above 178.660 thousand tons at the same age is assumed to reflect a *very strong year classes*. In the first case the catch is a 100% member of the set

of *very weak year classes*, while catches above 178.660 thousand tons are 100% members in the set of *very strong year classes*.

Table 3: Year class evaluations by membership degrees of sets of year class classification (in percent) at the quantile values provided in Table 2.

Catches	Year class evaluation in terms of percentage membership				
	Very weak (set 1)	Weak (set 2)	Medium (set 3)	Strong (set 4)	Very strong (set 5)
$\geq 5/6$ quantile	0	0	0	0	100
= 4/6 quantile	0	0	0	100	0
= 3/6 quantile	0	0	100	0	0
= 2/6 quantile	0	100	0	0	0
$\leq 1/6$ quantile	100	0	0	0	0

Catch values laying between the 1/6 and the 2/6 quantiles within their respective age groups are also partial members in the set of *very weak year classes*, but with less than 100% memberships. The exact membership degree depends on the distances to the two quantile values. Similarly, these catches also have partial memberships in the set of *weak year classes*. Zadeh (1983) refers to sets in which partial membership is possible as fuzzy sets. In this study any catch-at-age may be partial or full member of one or two fuzzy sets, according to membership degrees determined by linear relationships between the quantiles defining 0% and 100% memberships (respectively representing normalised membership degrees of 0 and 1) in each set (Table 3) as shown in Figure 3.

After the *fuzzification* of catches, which is to determine the membership degrees of each catch-at-age observation in the five defined sets, a *defuzzification* procedure is performed after the principle of Highest Membership Degree, selecting the set in which each year class' catch-at-age has its highest membership degree. By this procedure each catch-at-age is associated with a single set as illustrated in the top eleven rows of Figure 4. This simplification describes the strength of each year class in terms of eleven evaluations (except in the recent cases where the year class is still present in the stock). Other simple defuzzification procedures could be chosen (centre of gravity, centre of set intersections, centre of largest integrated set, all are possible candidates). Intuitively the highest membership degree seems to be most appealing in our case, but the choice of defuzzification method is one factor that should be further analysed and discussed. However, this study will employ to the principle of Highest Membership Degree.

Assign a numerical value to each of the five sets; Set 1 is the set of *very weak year classes*, set 2 the set of *weak year classes*, set 3 the set of *medium year classes*, set 4 the set of *strong year classes*, and set 5 is the set of *very strong year classes*. The 1943 year class, which was three years old while recruited to the fishable NEA cod stock in 1946, is for example evaluated by catch-at-age data to have the highest membership degrees in the following sets: $\{1, 1, 1, 4, 4, 5, 5, 5, 5, 5, 5\}$, listed from the lowest (3 years) to the highest age (13 years and older).

The second defuzzification procedure is to convert the age-structured vector of a year class – characterising year class strength at each catch-at-age value of the year class – to

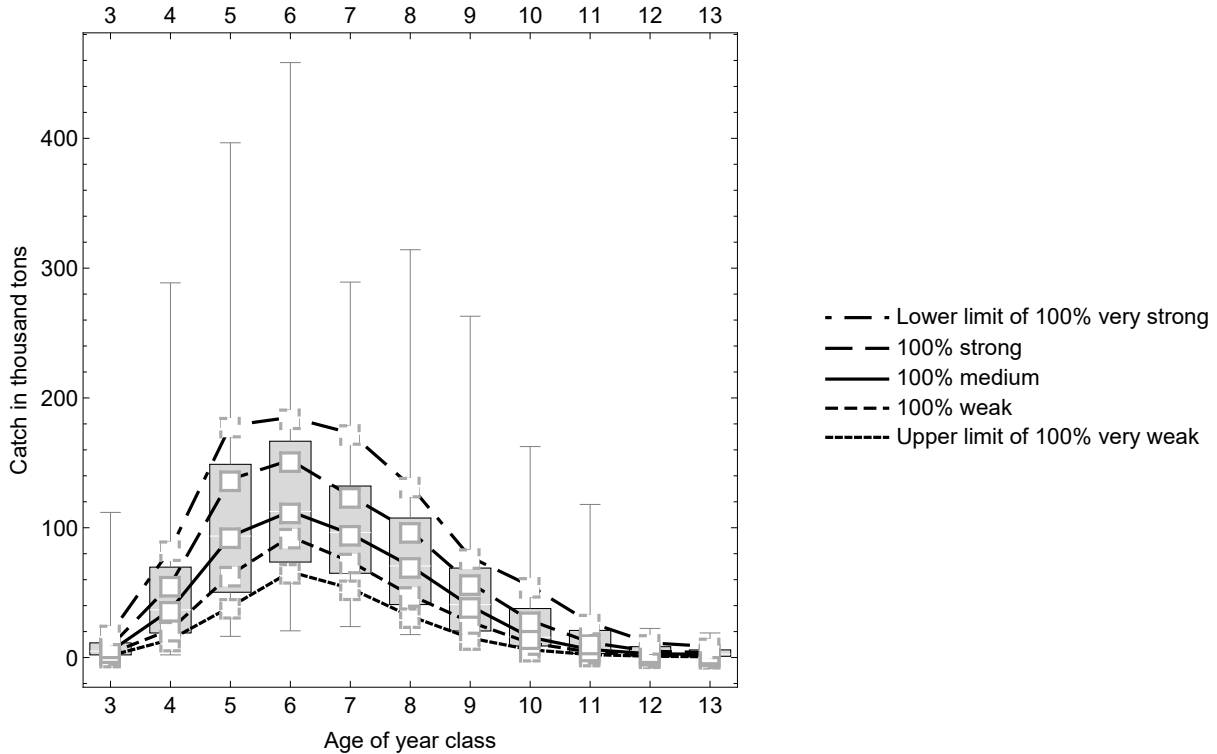


Figure 2: The box-whisker plot gives the distribution in NEA cod catches (in thousand tons) during the period 1946-2015 separated on year classes. The median values are indicated by white lines through the boxes. The five curves connect the different 1/6-quantiles of each year class, quantile values (from Table 2) are marked by white squares. Data sources are table 3.6 and table 3.8 in Anon. (2016), here presented in Table 1.

one single value, being the strength evaluation for the entire year class. As in the previous defuzzification procedure, where the simple principle of Highest Membership Degree where chosen, also here numerous possible defuzzification principles are available. Simple and transparent rule-based methods are preferable, and in this case we employ a successive pairwise evaluation of the elements in the year class vector following the rules displayed in Table 4. According to Figure 2, the largest cod catches are represented at ages between 4 and 9 year; hence, it seems reasonable to place more emphasis on these catches. It may also be reasonable to put a larger emphasis on early catches of a year class because of the increasing impact previous catches will have on the catches of older fish.

The chosen procedure therefore starts by pairing the set values of the oldest and youngest age group first (3 and 13+), followed by the pairing of (3 and 4), (4 and 5), (5 and 6), (6 and 7), (7 and 8), (8 and 9), (9 and 10) and (10 and 11). The second last value (in this case the catches of 12 year old cod) is omitted, systematically emphasising the catches on younger fish. The pairwise evaluation results in a new vector where the number of elements is reduced from 11 to 9: $\{3, 1, 1, 2, 4, 5, 5, 5, 5\}$. Then the same procedure is repeated, applying the same rules and the same pairing principle, until the vector contains only one digit. In our example, the sequence of vectors continues in this

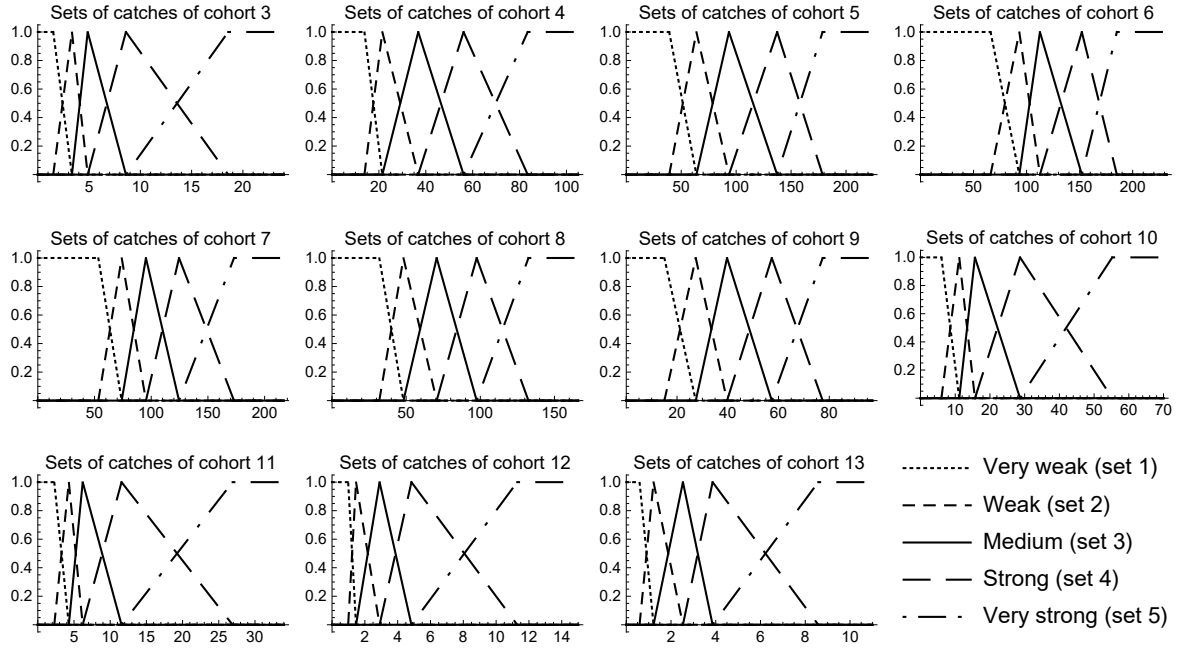


Figure 3: Membership degrees (vertical axes) for the five sets identified in Figure 2 for age groups from age 3 years to 13 years and older, as functions of catch-at-age (horizontal axes).

Table 4: Defuzzification rules employed to single out the fuzzy set of each year class by the use of sets of highest membership degrees for each age group. The numbers are referring to the sets presented in Figure 3; 1: *very weak*, 2: *weak*, 3: *medium*, 4: *strong* and 5: *very strong*.

$\{1, 1\} \rightarrow 1$	$\{1, 2\} \rightarrow 1$	$\{1, 3\} \rightarrow 2$	$\{1, 4\} \rightarrow 2$	$\{1, 5\} \rightarrow 3$
$\{2, 1\} \rightarrow 1$	$\{2, 2\} \rightarrow 2$	$\{2, 3\} \rightarrow 2$	$\{2, 4\} \rightarrow 3$	$\{2, 5\} \rightarrow 3$
$\{3, 1\} \rightarrow 2$	$\{3, 2\} \rightarrow 2$	$\{3, 3\} \rightarrow 3$	$\{3, 4\} \rightarrow 3$	$\{3, 5\} \rightarrow 4$
$\{4, 1\} \rightarrow 2$	$\{4, 2\} \rightarrow 3$	$\{4, 3\} \rightarrow 3$	$\{4, 4\} \rightarrow 4$	$\{4, 5\} \rightarrow 5$
$\{5, 1\} \rightarrow 2$	$\{5, 2\} \rightarrow 3$	$\{5, 3\} \rightarrow 4$	$\{5, 4\} \rightarrow 5$	$\{5, 5\} \rightarrow 5$

way: $\{4, 2, 1, 1, 3, 5, 5\}$, $\{5, 3, 1, 1, 2\}$, $\{3, 4, 2\}$, and $\{2\}$. The final digit – 2 – is assumed to represent an overall classification of the year class strength in terms of being a full member of the corresponding set, in our example this means that the 1943 year class is found to be a *weak year class*.

The lower row of Figure 4 displays the result after applying the second defuzzification method on all the year classes, employing the rules displayed in Table 4. The categorisation of year class strength of the period from year class 1943 to year class 2012 (recruited to the exploitable fish stock in 2015) then gives the following list for the NEA cod year class strength: $\{2, 2, 1, 1, 3, 5, 5, 5, 3, 1, 2, 4, 2, 2, 3, 4, 4, 2, 1, 3, 5, 5, 1, 1, 1, 1, 3, 5, 1, 3, 2, 1, 2, 1, 1, 1, 1, 1, 2, 3, 5, 1, 1, 1, 1, 2, 4, 3, 2, 1, 1, 3, 4, 2, 3, 2, 1, 4, 1, 3, 3, 5, 4, 2, 1, 1, 1, 1, 3, 2\}$. In the graphical representation of this vector in the lower row of Figure 4 each value (year class strength) is represented by different colours.

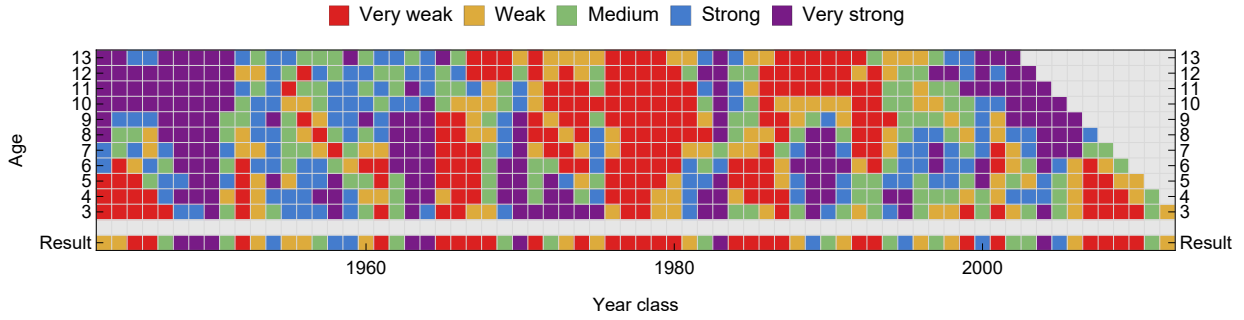


Figure 4: The top eleven rows display results after the first defuzzification procedure according to the principle of Highest Membership Degree for each year class (horizontal axis). The lower line (Result) shows the resulting aggregate after the second defuzzification procedure involving the rules displayed in Table 4.

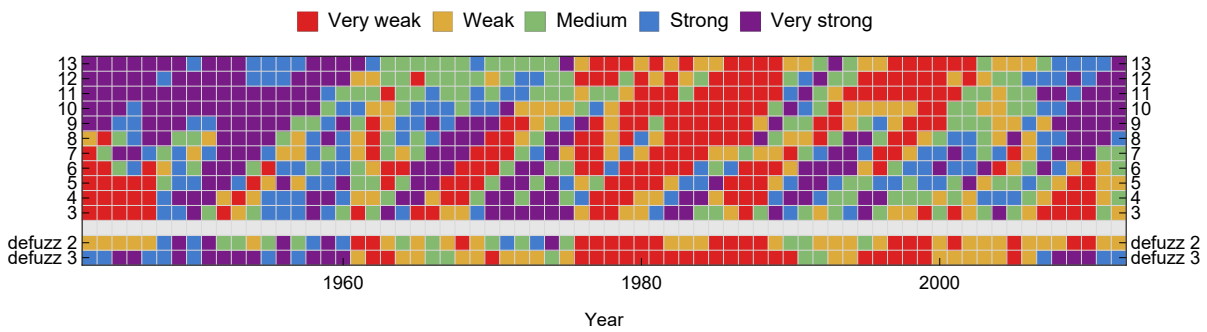


Figure 5: The top eleven rows display results after the first defuzzification procedure according to the principle of Highest Membership Degree for all year classes present in a given year (horizontal axis). The two lower lines (defuzz2 and defuzz3) show the resulting aggregates after the second and third defuzzification procedure, both employing the rules displayed in Table 4.

Up to now we have focused year class strength (e.g. recruitment strength) of each year class. Let us shift focus to now look at the assessment of relative stock size for each year, assuming this to be reflected in an aggregate of the catch-at-age evaluations of all year classes constituting the stock the given year.

The second defuzzification procedure aimed to minimise the impact from fishing by emphasising catches of young fish. A third defuzzification procedure is introduced by the opposite strategy; emphasising the catches of older fish. Previous catches on a year class will affect later catches of the same year class, and the third defuzzification procedure takes advantage of this knowledge. The procedure follows these steps: First, omitting the four youngest year classes before pairing the age groups (catch-at-age values of a given year) in the following way: (8 and 9), (7 and 8), (6 and 7), (5 and 6), (4, and 5), (3 and 4), (3 and 13+), (12 and 13+) and (11 and 12), employing the rules provided in Table 4. The procedure is then repeated as in the second defuzzification procedure until only one digit characterises the strength of the exploited stock that particular year. The assumption is that the difference between the second and third defuzzification procedures

gives a proxy of the fishing intensity. Both procedures utilise the same catch information, facing the same age composition in the stock. While the impact of fishing is believed to be low while nesting information from the younger to the older, it is assumed to be high while nesting information from the older to the younger fish.

Indicator values obtained from age distributed catches 1946 – 2015 by using the two defuzzification procedures are shown in the two lower rows of Figure 5 (note that the horizontal axis here refers to year, not year classes as in Figure 4). Since the difference between the two defuzzification procedures is assumed to reflect a fishing effort measure, we now make use of the aggregated catch data of each year to estimate a catch per unit of effort value, commonly considered to reflect stock strength (or stock density measure).

Results

The methodology described above is employing fuzzy set theory in its simplest version. The suggested defuzzification methods are illustrated by case studies to provide examples on how the theory could be implemented. Commercial catch-at-age data in the NEA cod fishery reveals a year class strength or recruitment pattern in striking correspondence with the recruitment strength estimated by stock assessments. In Figure 6 the two data sets are displayed in a common axes system. The correlation coefficient of the two data sets is 86%.

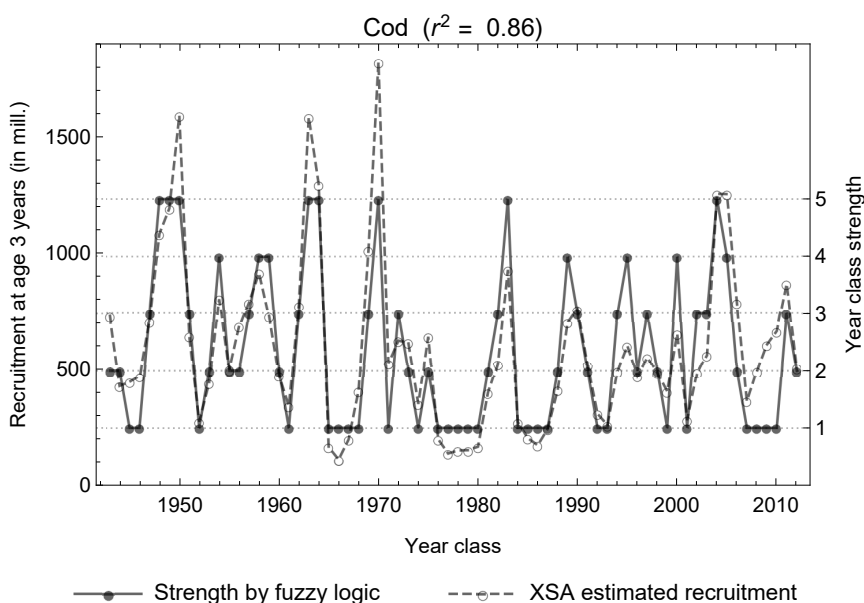


Figure 6: Results of the second defuzzification procedures as described in this paper (solid line) compared with corresponding estimates of year class strength (recruitment numbers) by stock assessments, Table 3.24a in Anon. (2016) (dashed line).

When comparing year class strengths obtained here by stock assessment estimates, a resolution of five sets (or strength categories) seems to be sufficient to grasp the essential

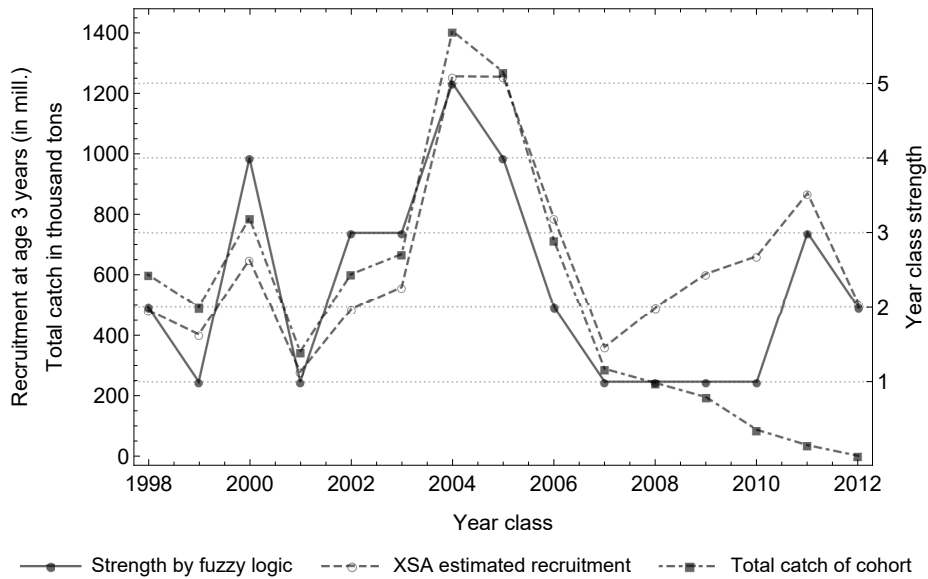


Figure 7: The figure shows the most recent (since 1998) year classes displayed in Figure 6 (solid and dashed lines) in addition to the aggregated catches of each year class (dotted line).

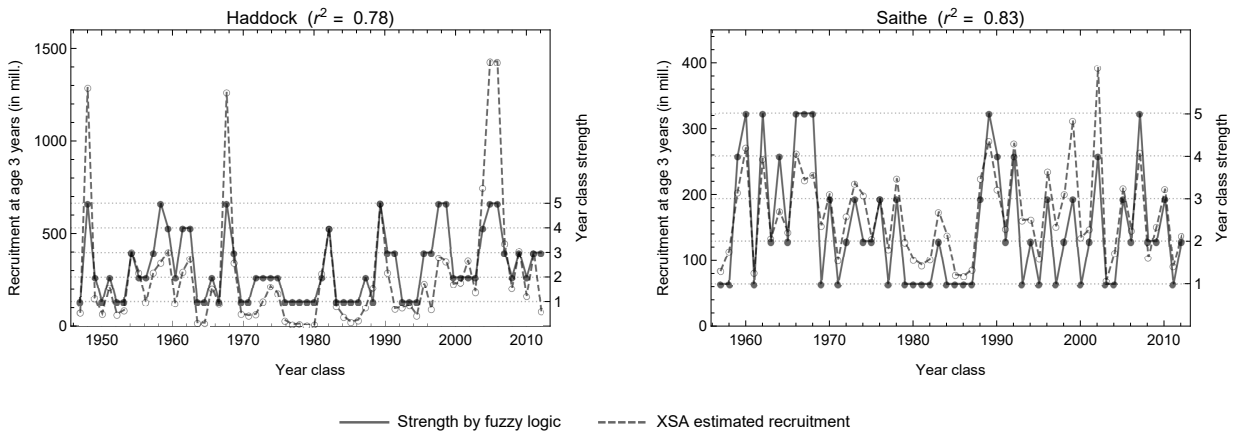


Figure 8: Results for Northeast Arctic haddock (tables 4.4 and 4.5 in Anon., 2016) and saithe (tables 5.5.1 and 5.5.2 in Anon., 2016) following the same procedure as for NEA cod in Figure 6.

fluctuations in recruitment strength over time. In the case of NEA cod, total catch by year classes correlates even stronger to the stock assessment estimates (Eide, 2016). This requires, however, a completed catch history of the year class in question; hence, it has less value for the management of a fishery. This is illustrated in Figure 7, which shows the most recent NEA cod year classes from Figure 6, in addition to total catches of the same year classes. The fuzzy logic estimated year class strengths correspond quite well to the stock assessments.

In addition to the case of the NEA cod stock, the suggested method of year class strength classification also has been applied on the catches of Northeast Arctic (NEA) haddock and saithe (Anon., 2016). Following the same procedure as described above

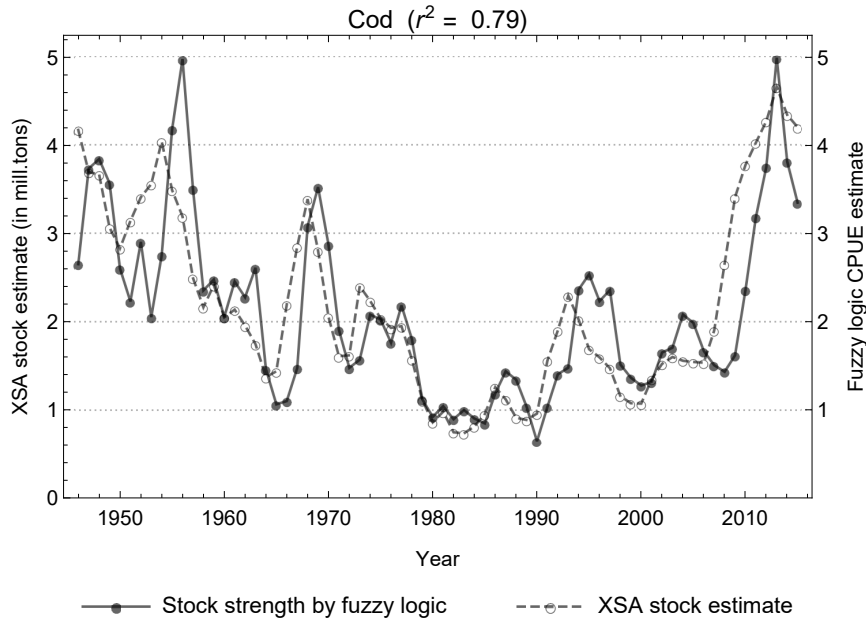


Figure 9: Total catches divided by the differences between the second and third defuzzification procedures (solid line), representing a stock size indicator (catch per unit of effort) compared with corresponding estimates of stock sizes by stock assessment 1946 – 2015, Table 3.24a in Anon. (2016) (dashed line).

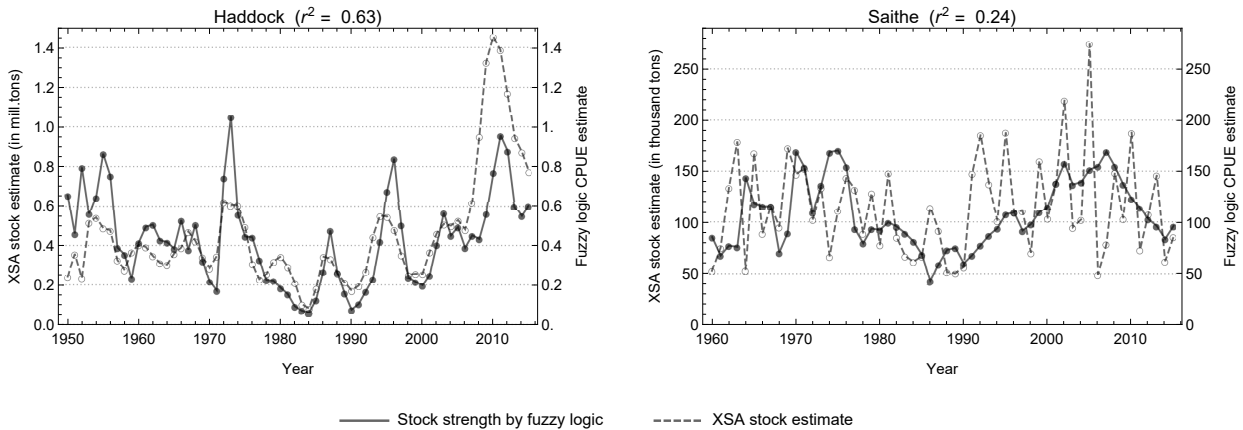


Figure 10: Total catches divided by the differences between the second and third defuzzification procedures (solid lines), representing a stock size indicator (catch per unit of effort) compared with corresponding estimates of stock sizes by stock assessment, Table 4.17 (haddock) and Table 5.5.5 (saithe) in Anon. (2016) (dashed lines).

78% of the stock assessment explained fluctuations in the haddock recruitment and a corresponding 83% of the saithe recruitment are explained by the methodology suggested here. The results are displayed in Figure 8.

Figure 9 shows how the sequences of recruitment strength evaluations may be developed further to a stock size indicator. The figure illustrates how a stock indicator obtained by dividing total catch with the difference between the second and third defuzzification procedures performs compared with the corresponding stock assessment estimates. 79%

of the stock variation found by stock assessments is explained by the fuzzy logic methodology in the case of the NEA cod stock. For haddock and saithe corresponding correlation coefficients are 63% and 24% (Figure 10).

Discussion

Fuzzy logic represents a way to structure data, information and knowledge in a non-algorithmic manner:

”Fuzzy logic provides a natural framework for the management of uncertainty in expert systems because – in contrast to traditional logical systems – its main purpose is to provide a systematic basis for representing and inferring from imprecise rather than precise knowledge. In effect, in fuzzy logic everything is allowed to be – but need not be – a matter of degree.” (Zadeh, 1983)

The estimating procedures presented here are not supposed to replace stock assessment methodologies. They rather represent possible ways of developing an alternative toolbox without the strict constraints in terms mathematical formulations and increasing demand for data beyond standard catch statistics. The alternative toolbox makes use of existing knowledge (precise and imprecise) as it develops, in addition to easily available data such as commercial catch statistics. As stated in the introductory part the cost associated with data sampling is only one of the issues calling for new methods to be developed.

In order to operationalise the increased focus on possible ecosystem consequences, which modern fisheries management is committed to do, rule based methods appear to be more promising. Combined inputs (indicator values) of direct observations fed into HCRs, while taking into consideration precautionary levels corresponding to precise and imprecise knowledge about system resilience and vulnerability, seems to represent a better approach to increased complexity in the object functions of fisheries management.

Compared with corresponding findings by the use of stock assessment, the results presented here provide surprisingly consistent year class strength evaluations. The task of employing fuzzy logic methodology to estimate stock size indicators is more challenging. The results from the stock size evaluation method suggested here are promising but the methodology needs to be further developed. Such a development should also include an investigation of using catch-at-age in terms of number of individuals rather than catch weights. Using both measures may improve the overall performance of the fuzzy logic method.

The stock size indicators for the NEA cod and haddock stocks fit quite well the stock assessments while in the case of the NEA saithe stock the fuzzy logic method fails to obtain the short-term large fluctuations identified by the traditional stock assessment methods

(Figures 9 and 10). The long-term trend captured by fuzzy logic is however in line with the stock assessment. A further discussion of the differences found by the two methods in the case of NEA saithe should also include a closer study of the stock assessment, in this case how the XSA methodology has been implemented. This is outside the scope of this paper but it could be noted that according to the relatively stable recruitment dynamics of the stock (Figure 8) the large fluctuations in stock size at first sight are surprising. The consistency between the two obviously is linked to the fact that the overall saithe stock size, according to stock assessments, is far below the levels of NEA cod and haddock.

From Figure 9 it seems to be a slight delay in time between the fuzzy logic method and the NEA cod stock assessment. This delay may be related to a delay between fishing effort and the impact it has on the stock. Another – or additional – explanation may be that while the stock assessment provides an evaluation of all year classes, the indicator obtained by fuzzy logic only consider the year classes represented in the fishery. A further refinement with regard of possible time lag issues may also contribute in improving the method.

This paper illustrates how fuzzy logic techniques could be used to identify stock properties commonly utilised as HCR indicators, substituting model-based indicators. Today catch data (observations) are channelled to the HCRs through non-transparent models. Heuristic expert system procedures similar to those presented in this paper could in the future be an integral part of sets of HCRs. Use of catch-at-age statistics as direct inputs to sets of HCRs will provide more explainable *Lines-of-reasoning*. The evaluation of the state of the stock could be one step in a rule-based line-of-reasoning in producing fisheries management decisions (or advices).

A full implementation of a fuzzy logic based heuristic expert system for the management of fisheries involves several issues not covered here. Obviously the performance of any new set of HCRs to be used in a fishery needs to be thoroughly evaluated before taken into use. Selection of indicators depends on the management objectives and how these should be embedded into the HCRs. Ideally all indicators should be measurable in order to reduce the problem of non-transparency and to be organised in the manner of a comprehensible *Line-of-reasoning*, containing heuristic rules based on expert knowledge and stated objectives of the fishing activity. Also non-biological indicators, such as economic performance and other social factors, could be included in the set of rules constituting the HCRs.

The simple rule-based pattern of the control system also opens for learning and then the possibility of adjusting the rules according to new knowledge gained by using the control system. A fully adaptive heuristic control system also includes the possibility of adding indicators, as long as these could be measured through observations. Such ideas also open for the possibility of developing HCRs through sets of meta-rules, a control system which in principle constitute a system of artificial intelligence (AI) with

the capacity of learning.

The aim of this paper has been to investigate the ability of simple, intuitive rules, providing fisheries managers with essential information about the state of the stock. The results are promising even though there may be a long way to go until such ideas can make their way into the fairly well-functioning management procedures of modern fisheries today. Perhaps the first practical use of fully developed rule-based expert systems rather will be in less data-rich fisheries where the management procedures today are poorly developed.

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